Unlocking the Invisible Urban Traffic Dynamics under Extreme Weather: A New Physics-Constrained Hamiltonian Learning Algorithm

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Abstract

Urban transportation systems face increasing resilience challenges from extreme weather events, but current assessment methods rely on surface-level recovery indicators that miss hidden structural damage. Existing approaches cannot distinguish between true recovery and "false recovery," where traffic metrics normalize, but the underlying system dynamics permanently degrade. To address this, a new physics-constrained Hamiltonian learning algorithm combining "structural irreversibility detection" and "energy landscape reconstruction" has been developed. Our approach extracts low-dimensional state representations, identifies quasi-Hamiltonian structures through physics-constrained optimization, and quantifies structural changes via energy landscape comparison. Analysis of London's extreme rainfall in 2021 demonstrates that while surface indicators were fully recovered, our algorithm detected 64.8% structural damage missed by traditional monitoring. Our framework provides tools for proactive structural risk assessment, enabling infrastructure investments based on true system health rather than misleading surface metrics.

1 Introduction

Urban transportation systems face unprecedented resilience challenges from accelerating urbanization and increasing extreme weather events [1, 2]. Their growing complexity makes them vulnerable to cascading failures and prolonged service disruptions [3, 4], with restoration processes proving lengthy and expensive [5, 6]. Current resilience assessment methods rely on surface-level recovery indicators such as traffic flow restoration rates and connectivity measures [7]. These approaches assume that numerical recovery equates to system recovery—if traffic volumes return to pre-event levels, the system is deemed fully restored [8]. However, this approach cannot detect whether extreme events have caused permanent structural damage to the system's underlying dynamical architecture, leading to "false recovery" phenomena where surface metrics normalize but fundamental system

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behavior has been altered. This limitation reflects a broader challenge in complex systems physics, where macroscopic observables may appear stable while underlying dynamical structures have been permanently changed [9, 10]. Current resilience quantification approaches lack calibration across different stress scenarios [11, 12], and empirical observations during disasters remain limited [13].

Recent advances in physics-informed machine learning offer new possibilities for understanding complex system dynamics. Hamiltonian Neural Networks can learn conservation laws from data while maintaining physical consistency [14, 15], and port-Hamiltonian approaches show promise for modeling structural dynamics with energy-preserving properties [16, 17]. However, existing algorithms face critical gaps when applied to urban transportation systems: 1) structural invisibility—current methods cannot detect hidden changes in underlying energy landscapes after extreme events[18, 19, 20], 2) false recovery detection failure—no algorithm can distinguish between true recovery and cases where surface metrics normalize but fundamental architecture remains altered[21, 8], and 3) multi-scale integration deficiency—existing approaches cannot simultaneously capture both quasi-Hamiltonian conservation properties and dissipative effects across temporal scales[15, 16]. To address these limitations, we introduce "structural irreversibility" for urban transportation systems—the phenomenon where surface indicators recover while the system's underlying dynamical architecture remains permanently altered. Unlike traditional resilience metrics focusing on functional recovery [22, 23], we develop a novel Physics-Constrained Hamiltonian Structure Learning (PCHSL) algorithm that learns the system's intrinsic "energy landscape" to diagnose structural health changes invisible to conventional monitoring. We validate this framework through analysis of London's transportation network during the October 5, 2021 extreme rainfall, demonstrating that while surface indicators fully recovered, the system's Hamiltonian structure underwent significant and persistent changes.

2 Methods

2.1 Problem Formulation

Traditional resilience assessment methods face a fundamental limitation: they monitor surface phenomena (flow rates, speeds, connectivity) but cannot detect changes in the underlying organizational principles that govern system behavior [21, 13]. This is analogous to observing that a ball returns to a similar position without knowing whether the landscape it rolls on has been permanently altered. We develop a novel PCHSL algorithm to solve this structural invisibility problem. Our algorithm models urban traffic systems as dynamical systems with discoverable energy-based structures. Transportation networks exhibit conservation-like properties (flow conservation at intersections) and natural equilibrium-seeking behavior (stable traffic patterns), suggesting they may follow quasi-Hamiltonian dynamics [14, 16]. The core innovation of PCHSL algorithm is learning the "energy landscape"–the underlying structural rules that determine how the system evolves and responds to disturbances [15]. Given traffic time series data $\mathbf{X} \in \mathbb{R}^{N \times T}$ from N road segments, we hypothesize the system follows:

$$\dot{\mathbf{z}} = \mathbf{J}\nabla H(\mathbf{z}) + \mathbf{D}(\mathbf{z}) \tag{1}$$

where $\mathbf{z} \in \mathbb{R}^d$ represents the system's low-dimensional state, $H(\mathbf{z})$ is the Hamiltonian function encoding the energy landscape, $\mathbf{J} = \begin{bmatrix} 0 & 1 \\ -1 & 0 \end{bmatrix}$ is the symplectic matrix preserving energy structure, and $\mathbf{D}(\mathbf{z})$ captures dissipative effects from friction and control interventions. The Hamiltonian $H(\mathbf{z})$ acts as a "topographic map" where valleys represent stable operating states and hills represent unstable configurations. The system naturally evolves toward energy minima (stable traffic patterns), following gradients of this landscape. Crucially, the PCHSL algorithm detects when extreme events alter the landscape structure–changing the locations, depths, or shapes of these valleys–indicating that the system's fundamental behavior is permanently modified, even if surface metrics appear to recover. Our algorithm reveals such structural irreversibility by comparing energy landscapes before and after extreme events, uncovering hidden changes that traditional monitoring cannot capture.

2.2 The PCHSL Algorithm: A Three-Module Architecture

The PCHSL algorithm addresses the challenge that real transportation systems operate in high-dimensional space, making direct Hamiltonian analysis intractable. The algorithm consists of three core computational modules: **Module 1** applies PCA[24] and t-SNE[25] to extract essential dynamics:

$\mathbf{z}_t = \mathbf{U}_d^T \mathbf{x}_t$, where $\mathbf{U}_d$ contains the first $d = 2$ principal components. **Module 2** implements our core algorithmic innovation: physics-constrained optimization to learn the Hamiltonian structure. Our algorithm parameterizes the Hamiltonian as: $H(z_1, z_2) = \sum_{i,j} h_{ij} z_1^i z_2^j$ and compute derivatives using finite differences: $\dot{z}_i(t) = \frac{z_i(t+\Delta t) - z_i(t-\Delta t)}{2\Delta t}$. The learning objective enforces Hamiltonian structure:

$$\mathcal{L}(\boldsymbol{\theta}) = \frac{1}{T} \sum_{t=1}^{T} |\dot{\mathbf{z}}_t - \mathbf{J} \nabla H(\mathbf{z}_t; \boldsymbol{\theta})|^2 + \lambda \mathcal{R}(\boldsymbol{\theta}) \tag{2}$$

Module 3 provides uncertainty quantification through Bayesian inference with Gaussian priors and Hamiltonian Monte Carlo sampling for robust parameter estimation of the learned energy landscape.

2.3 Structural Irreversibility Detection

The central hypothesis of our PCHSL algorithm is that extreme events may permanently alter the energy landscape while leaving surface traffic patterns apparently unchanged. To test this hypothesis, we learn separate Hamiltonians H_{before} and H_{after} for pre- and post-event periods, then systematically compare their structural properties. We quantify structural differences by measuring how much the energy landscapes have changed across the relevant state space:

$$d(H_{\text{before}}, H_{\text{after}}) = \int_{\Omega} |H_{\text{before}}(\mathbf{z}) - H_{\text{after}}(\mathbf{z})|^2 d\mathbf{z} \tag{3}$$

This metric captures fundamental changes in the "topographic map": whether valleys have shifted, deepened, or become shallower, regardless of whether traffic flows have returned to similar aggregate levels. To enable meaningful comparison across different systems and events, we normalize this distance to obtain the structural irreversibility index

$$\text{SIR} = \frac{d(H_{\text{before}}, H_{\text{after}})}{\|H_{\text{before}}\|_2} \tag{4}$$

This threshold reflects significant landscape deformation that would measurably affect system stability and future response patterns.

3 Results

We analyze London's transportation network during the extreme rainfall event of October 5, 2021, using traffic flow data from 11,821 road segments collected at hourly intervals. The dataset spans 14 days (7 days before and 7 days after the event), totaling 3,971,856 data points with rainfall intensity of 42 mm/h (Fig.1a). Our data processing pipeline demonstrates effectiveness in capturing the system's underlying dynamics (Fig.1b). The daily traffic pattern comparison reveals apparent recovery in surface-level metrics, with both pre- and post-event periods showing similar diurnal patterns. However, the traffic flow heatmap indicates subtle but persistent changes in temporal-spatial distribution patterns. Our two-stage dimensionality reduction (PCA to 50 dimensions retaining 77.5% variance, then t-SNE to 2D) successfully captured essential system dynamics. Our physics-constrained optimization identifies quasi-Hamiltonian structures, achieving 92.96% and 98.81% convergence improvement for pre- and post-event periods respectively. The phase space trajectory analysis (Fig.1c) reveals striking differences in system behavior. The pre-event trajectories show more dispersed patterns with broader exploration of the state space, while post-event trajectories exhibit more constrained dynamics with clear convergence toward specific regions. The system velocity comparison demonstrates reduced dynamical variability in the post-event period, suggesting the emergence of more regular but fundamentally different organizational patterns. The learned energy functions reveal profound structural transformation. The pre-event Hamiltonian takes the form:

$$H_{\text{before}}(z_1, z_2) = 0.045 - 0.095z_2 + 0.149z_2^2 - 0.046z_1 - 0.236z_1z_2 + 0.058z_1^2$$

while the post-event function becomes:

$$H_{\text{after}}(z_1, z_2) = 0.070 + 0.082z_2 + 0.044z_2^2 - 0.192z_1 + 0.002z_1z_2 - 0.008z_1^2$$

The energy landscape transformation (Fig.1d) provides visual evidence of structural irreversibility. The before-event energy landscape shows a complex topography with multiple local minima and

smooth gradients. In contrast, the after-event landscape exhibits a fundamentally different structure with altered valley locations and modified energy barriers. Most critically, the difference map reveals systematic shifts in energy distribution, with some regions experiencing energy increases up to +60 units while others show decreases down to -300 units. Despite apparent surface-level recovery in daily traffic patterns, our structural analysis reveals significant hidden damage. The energy landscape distance $d(H_{\text{before}}, H_{\text{after}})$ yields a Structural Irreversibility Index of SIR $= 0.695$, exceeding our detection threshold by nearly an order of magnitude. The coefficient sign changes in critical terms indicate fundamental alterations in dynamical coupling mechanisms. Our framework estimates a 64.8% false recovery component, demonstrating that conventional monitoring approaches miss approximately two-thirds of actual structural damage. The phase space analysis further confirms this structural transformation. While pre-event trajectories exhibit continuous flux behavior without stable attractors, the post-event system develops defined convergence patterns toward specific state space regions. This represents a qualitative phase transition from a system characterized by broad exploration to one with constrained dynamics, providing quantitative evidence that extreme weather events can induce permanent organizational transitions in urban traffic systems that remain completely invisible to traditional surface-level monitoring approaches.

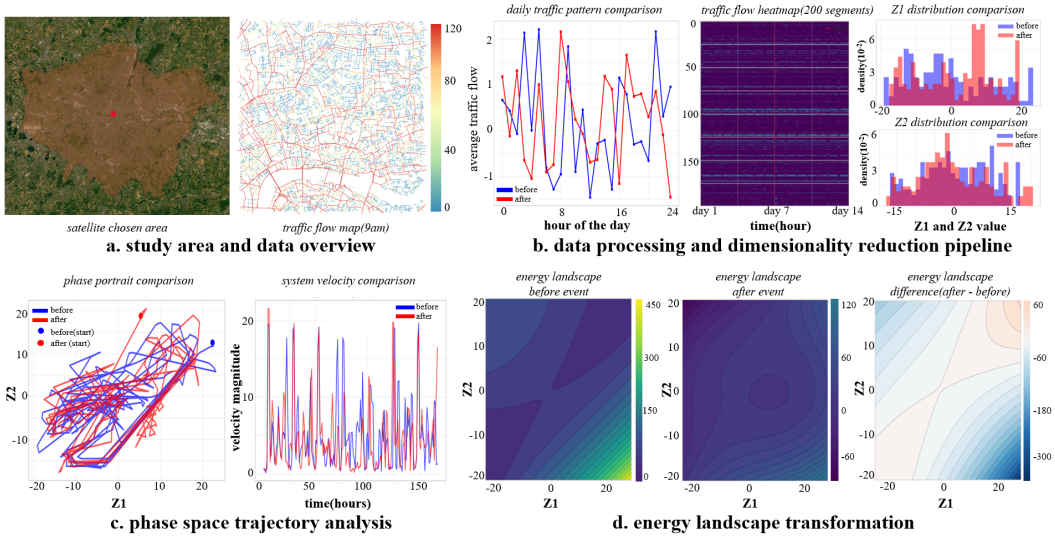

Figure 1: Structural irreversibility detection in London's transportation system under extreme rainfall

4 Discussion

The proposed algorithm provides the first quantitative evidence that extreme weather events can cause structural irreversibility in urban transportation systems, fundamentally challenging the assumption that surface-level recovery indicates true system restoration. The algorithm's detection of 64.8% false recovery component represents a critical blind spot in current resilience assessment practices, revealing that traditional metrics systematically miss nearly two-thirds of actual structural damage. Our algorithm's identification of coefficient sign changes and energy landscape transformation provides converging computational evidence for genuine dynamical regime change. Most significantly, the algorithm successfully detects the emergence of stable equilibria, indicating a qualitative phase transition in system self-organization, with implications for future perturbation responses. Our physics-constrained algorithmic framework demonstrates the value of embedding conservation principles into machine learning, providing mechanistic insight into structural changes invisible to conventional monitoring approaches. The concept of structural irreversibility, enabled by our algorithm, may extend to other critical infrastructure systems where surface metrics similarly mask permanent organizational changes. Algorithm limitations include single-event analysis and quasi-Hamiltonian assumptions. Future algorithmic developments should validate across diverse contexts and develop real-time monitoring capabilities.

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