

Routing-induced phase transitions in traffic efficiency of non-Markovian dynamics

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(Received 20 September 2025; accepted 8 January 2026; published 22 January 2026)

Complex networks provide a natural framework for modeling transportation systems, capturing the interplay between flow dynamics and topology structure. We introduce a non-Markovian traffic model in which the traversal time of each link depends on both its inherent heterogeneous travel time and congestion delays caused by simultaneous usage. Agents may adopt one of two intuitive routing strategies: the shortest-time path (TSP) or the shortest-distance path (GSP). We derive an analytical expression for the system-wide average travel time as a function of routing preference. Remarkably, our analysis reveals three distinct efficiency phases, fast is fast, Parrondo, and slow is fast, resulting from the trade-off between global travel time savings and congestion delays induced by load imbalance. Theoretical conditions for the emergence of each phase are established and corroborated by numerical simulations across diverse networks. Rather than claiming that routing alone resolves congestion, our results reveal when and why routing preferences can shift the system between fundamentally different efficiency phases, providing a statistical-physics foundation for understanding and optimizing transport in communication, logistics, and urban-mobility networks.

DOI: [10.1103/rpfs-bvc7](https://doi.org/10.1103/rpfs-bvc7)

Introduction. Transportation processes, ranging from Internet data transmission [1] and supply chain logistics [2] to human mobility [3], are pervasive in modern society, displaying rich spatiotemporal complexities that span from microscopic flow distributions to macroscopic phase transitions [4–7]. Complex network theory provides a unifying framework for modeling these systems by abstracting physical entities into nodes and their interactions into edges, thereby capturing the essential dynamics of agent flow [8,9]. Driven by this paradigm, research into traffic dynamics on networks has expanded considerably, evolving from single-layer to multilayer structures [10–12], from routing strategies to resource allocation mechanisms [13–16], and from deterministic models to stochastic descriptions [17,18]. These advances continue to deepen our understanding of real-world transportation systems and provided theoretical guidance for their optimization.

Modeling traffic flow on networks typically hinges on how agent movements are updated across time and space for multiple origin-destination pairs [19,20]. A widely used simplification assumes instantaneous, Markovian dynamics, in which an agent moves from one node to a neighbor in a single fixed time step [21]. This assumption, however, suppresses

two fundamental sources of temporal heterogeneity that characterize real transport processes: (1) inherent traversal times, determined by link-specific properties such as physical length or bandwidth, and (2) congestion-induced delays, which prolong the time an agent must remain on a link when many others attempt to use the same resource concurrently. Because the actual dwell time on a link depends both on its identity and on the evolving global traffic load, transitions have variable duration that depends on the system state, rendering the dynamics intrinsically non-Markovian. These effects are ubiquitous: Delivery times in logistics scale with both distance and workload; data transmission delays depend on physical path length and bandwidth contention; and urban travel times are shaped by road length and traffic jams. Incorporating such state-dependent traversal times is therefore essential for constructing realistic traffic models and for revealing the dynamical regimes that arise from the competition between intrinsic heterogeneity and congestion.

Here, we develop a general framework for non-Markovian traffic dynamics that integrates link-dependent inherent travel times with flow-induced congestion delays. We show that routing strategies in this setting give rise to distinct efficiency phases, including Braess-like paradoxes. Unlike previous studies based on microscopic models such as the asymmetric simple exclusion process or the Nagel-Schreckenberg model [22–25], where congestion emerges from site-level blocking, finite-capacity exclusion, or discrete update rules, the mechanism here arises from state-dependent traversal times shaped jointly by heterogeneous link properties and flow-induced dwell-time extensions. In this framework, congestion is produced not by hard-capacity constraints but by dynamically

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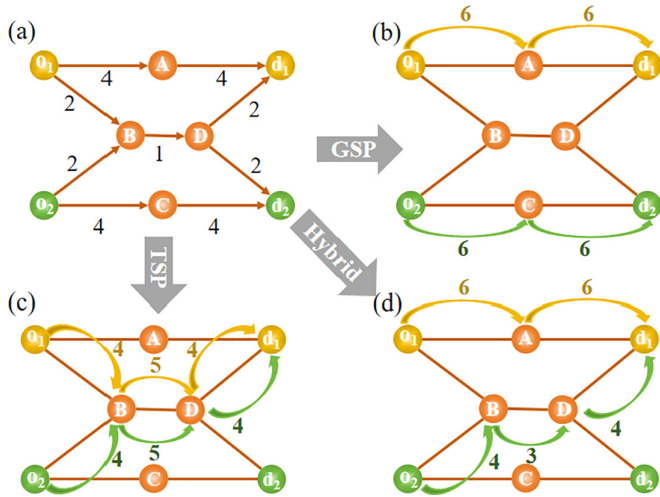


FIG. 1. Schematic of the proposed non-Markovian traffic dynamics model. (a) A transportation network of eight nodes, with two agents departing from o_1 and o_2 to destinations d_1 and d_2 , respectively. Numbers adjacent to links indicate the inherent travel time τ_0^e . Panels (b)–(d) show the paths and resulting average travel times $\langle T \rangle$ when both agents use the geographically shortest path (GSP), the time shortest path (TSP), and a mixed strategy, respectively. Paths are indicated by arrows, with actual travel times (including congestion) shown alongside. Here, the congestion coefficient is $\lambda = 2$. Note that greedy use of TSP in panel (c) leads to congestion and increased travel time, whereas hybrid routing in panel (d) alleviates congestion and improves overall efficiency.

varying traversal times along complete paths. Analytical theory and numerical simulations jointly identify the conditions under which the resulting phases emerge, offering insights into the fundamental limits of transport efficiency in complex networks.

Model and method. We represent the transport system as a network $\Gamma = (V, E)$ with N nodes $V = \{v_1, v_2, \dots, v_N\}$ and M links $E = \{e_1, e_2, \dots, e_M\}$, yielding an average degree $\langle k \rangle = M/N$. As illustrated in Fig. 1(a), at each time step every node generates countable agents whose destinations are chosen uniformly at random. Note that an agent is measured in arbitrary units: a demand of 1 may correspond to 100 data packets, 1000 parcels, or 10 vehicles, depending on the system under study. The traversal time of a link reflects both its intrinsic properties and the congestion experienced at the moment of entry. Accordingly, when an agent enters link e at time t , its traversal time is assigned as

$$\tau^e(t) = \tau_0^e + \lambda f^e(t), \quad (1)$$

where λ denotes the congestion sensitivity. Here, $f^e(t)$ represents the instantaneous inflow to link e at time t , namely, the number of agents that enter link e during the same time step. Once assigned, the traversal time remains fixed for the agent throughout the traversal of the link, even if other agents subsequently enter or leave the link. The inherent travel time τ_0^e captures link heterogeneity and is drawn independently and uniformly from $[1, 2\bar{\tau}_0 - 1]$, with $\bar{\tau}_0$ denoting the mean free-flow travel time across links. Larger $\bar{\tau}_0$ implies stronger variability in inherent travel times.

We emphasize that Eq. (1) renders the dynamics fundamentally non-Markovian. In a Markovian traffic model, each hop occurs in one discrete step and the transition kernel does not depend on the accumulated waiting time. Here, however, the actual time spent on a link varies across links via τ_0^e and depends on the instantaneous flow $f^e(t)$, which fluctuates over time as a consequence of agent injection, heterogeneous traversal times, and congestion-induced dwell-time effects. Consequently, an agent's transition from one node to the next has a variable duration dictated by the evolving global state, breaking the Markov assumption. This non-Markovianity is not a technical detail but a necessary ingredient for producing the efficiency transitions reported in this work.

For an origin-destination pair $(o, d) \in OD = \{o \rightarrow d \mid o, d \in V, o \neq d\}$, a route is denoted as a sequence $L(o \rightarrow d) = o \rightarrow e_1 \rightarrow e_2 \rightarrow \dots \rightarrow e_m \rightarrow d$, with $e_i \in E$. Since routing decisions dictate how flows are distributed across the network, they are central to congestion and efficiency. To contrast different optimization principles, we consider two canonical strategies:

(1) *Time shortest path.* Minimizes the total intrinsic travel time, $\min \sum_{l=1}^m \tau_{e_l}^0$, optimal in congestion-free settings [Fig. 1(b)].

(2) *Geographically shortest path.* Minimizes the hop count, $\min m$, thereby reducing exposure to congestion [Fig. 1(c)].

To capture heterogeneous behavior, each agent independently selects TSP with probability p and GSP with probability $1 - p$. We then analyze the emergent system-wide transport efficiency under such hybrid routing [Fig. 1(d)].

The model dynamics proceeds in discrete time steps and follows an event-driven update rule. At each time step, every node generates r agents with randomly assigned destinations. Upon generation, each agent selects a routing strategy (TSP or GSP) according to the prescribed probability p and determines its route accordingly. When an agent reaches the entrance of a link, it enters the link and is assigned a traversal time according to Eq. (1). The agent then remains on the link for the assigned duration and exits the link upon completion of the traversal. Agents reaching their destination are removed from the system. The instantaneous inflow $f^e(t)$ is updated at each time step by counting the number of agents entering link e during that step. This microscopic dynamics generates time-dependent link flows, whose stationary averages are used in the analytical approximation introduced below.

Theoretical analysis. To quantify transport efficiency, we employ the average travel time $\langle T \rangle$, theoretically calculated as

$$\langle T \rangle = \frac{\sum_{od \in OD} \sum_{e \in E} f_{od}^e \tau_{od}^e}{\sum_{od \in OD} f_{od}}, \quad (2)$$

where f_{od} is the total flow from origin o to destination d , f_{od}^e denotes the fraction of that flow traversing link e , and τ_{od}^e is the time spent on link e , which depends on concurrent flows from other OD pairs. To derive an analytic expression, we introduce the link betweenness centrality [26]. For a given OD pair (o, d) , under routing strategy L , the betweenness of link e is $b_{od}^{L,e} = h_{od}^{L,e} / g_{od}^L$, where g_{od}^L is the total number of admissible paths from o to d and $h_{od}^{L,e}$ counts those passing through e .

Summing over all OD pairs yields the total link betweenness $b^{L,e} = \sum_{od \in OD} b_{od}^{L,e}$, which captures the expected load on link e under the specified routing strategy L .

Within a mean-field approximation, the effective betweenness under mixed routing, parameterized by p , is given by

$$b_{od}^{p,e} = pb_{od}^{T,e} + (1-p)b_{od}^{G,e}, \quad (3)$$

$$b^{p,e} = pb^{T,e} + (1-p)b^{G,e}. \quad (4)$$

For unit agent generation ($r = 1$), the flows on link e contributed by OD pair (o, d) and by all other pairs are, respectively,

$$f_{od}^{p,e} = \frac{1}{N-1} b_{od}^{p,e}, \quad (5)$$

$$\begin{aligned} \langle T \rangle_p &= \frac{\langle k \rangle}{N-1} \left\{ \left\langle (\tau_0^e + \lambda)(pb^{T,e} + (1-p)b^{G,e}) \right\rangle_e + \frac{\lambda r}{N-1} \left\langle (pb^{T,e} + (1-p)b^{G,e})^2 \right\rangle_e - \frac{\lambda r}{N-1} \left\langle \sum_{od \in OD} (pb_{od}^{T,e} + (1-p)b_{od}^{G,e})^2 \right\rangle_e \right\} \\ &\approx \frac{\langle k \rangle}{N-1} \left\{ \left\langle (\tau_0^e + \lambda)(pb^{T,e} + (1-p)b^{G,e}) \right\rangle_e + \frac{\lambda r}{N-1} \left\langle (pb^{T,e} + (1-p)b^{G,e})^2 \right\rangle_e \right\}. \end{aligned} \quad (7)$$

This approximation is justified because $f_{od}^{p,e} \ll f^{p,e} = f_{od}^{p,e} + f_{od}^{p,e}$, implying that the sum of squared OD-specific betweennesses is negligible compared to the square of the total betweenness. The approximation becomes increasingly accurate for larger networks, as the contribution of individual OD flows to link congestion vanishes with N . We validate Eq. (7) using Monte Carlo simulations on Barabási-Albert (BA) networks [28], considering varying levels of traffic loads and congestion sensitivity (Fig. 2).

We next examine how routing preferences shape congestion patterns and overall traffic efficiency. Since routing preferences continuously interpolate between the two extremes, the optimal choice can be located by examining how $\langle T \rangle_p$ changes with p . Differentiating with respect to p yields

$$\begin{aligned} \frac{d\langle T \rangle_p}{dp} &= \frac{\langle k \rangle}{N-1} \left[\frac{2\lambda r}{N-1} p \langle (\Delta b^e)^2 \rangle_e - \left\langle \left(\tau_0^e + \lambda - \frac{2\lambda r}{N-1} b^{G,e} \right) \Delta b^e \right\rangle_e \right], \end{aligned} \quad (8)$$

where $\Delta b^e = b^{G,e} - b^{T,e}$. Setting this derivative to zero gives the critical routing preference

$$p_c = \frac{\left[\langle (N-1)(\tau_0^e + \lambda) + 2\lambda r b^{G,e} \rangle_e \Delta b^e \right]_e}{2\lambda r \langle (\Delta b^e)^2 \rangle_e}. \quad (9)$$

Since p is constrained to the interval $[0, 1]$, the actual optimal routing preference becomes

$$p_o = \begin{cases} 0, & \text{if } p_c \leq 0, \\ p_c, & \text{if } 0 < p_c < 1, \\ 1, & \text{if } p_c \geq 1. \end{cases} \quad (10)$$

This theoretical prediction for p_o [Eq. (10)] is confirmed by simulations (see Fig. S1 in the Supplemental Material [27]). Depending on p_o , three distinct dynamical regimes emerge:

$$f_{od}^{p,e} = \frac{1}{N-1} (b_{od}^{p,e} - b_{od}^{p,e}). \quad (6)$$

The expressions in Eqs. (5) and (6) are obtained only after ensemble averaging in the stationary regime and within a mean-field approximation; they therefore represent coarse-grained descriptors of the emergent steady-state flows (betweenness-like quantities), not fixed structural inputs.

These quantities capture how traffic loads are distributed across links and thus determine the congestion delay experienced by each OD pair (see the Supplemental Material [27] for details). Substituting them into Eq. (2) yields a closed-form expression for the average travel time:

(1) *FIF (fast is fast)*. When $p_o = 1$, intuition holds, favoring the time-based shortest path speeds up the system, and more “greedy” agents improve overall efficiency.

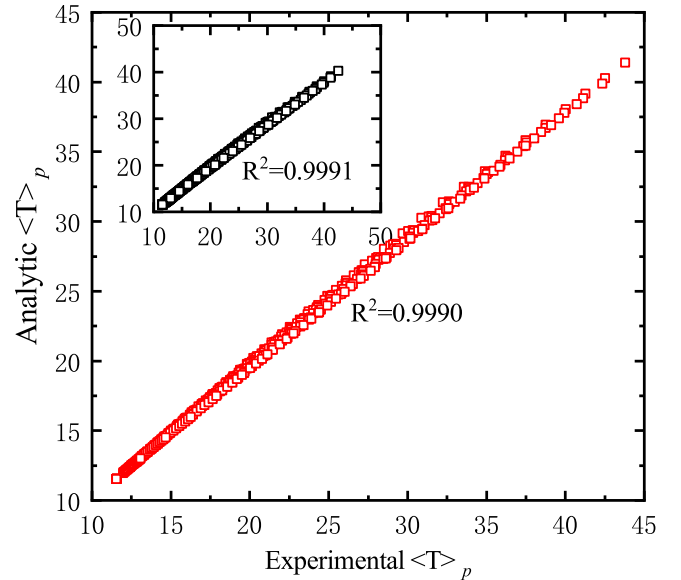


FIG. 2. Validation of the analytic expression for the average travel time $\langle T \rangle_p$ [Eq. (7)] against Monte Carlo simulations on Barabási-Albert networks. Each point corresponds to one of 400 distinct configurations with traffic level $r \in [0.1, 2]$ and congestion sensitivity $\lambda \in [0.1, 2]$. The inset shows the correlation between simulated travel times and the full theoretical prediction (without approximation) from Eq. (S6) in the Supplemental Material [27]; the coefficient of determination R^2 quantifies the agreement. Simulations were performed with routing ratio $p = 0.5$ on a network of size $N = 1000$, average degree $\langle k \rangle = 10$, and mean inherent link travel time $\bar{\tau}_0 = 5$.

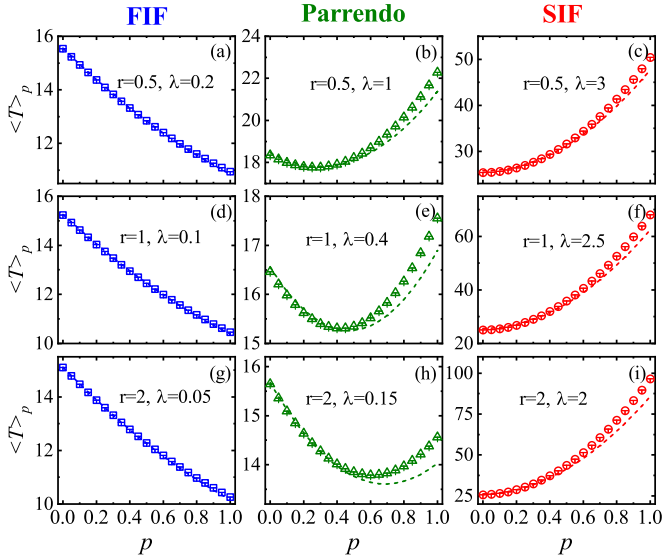


FIG. 3. Average travel time $\langle T \rangle_p$ as a function of routing preference p for various traffic levels r and congestion sensitivities λ . Each row corresponds to a fixed r with increasing λ ; each column shows how $\langle T \rangle_p$ varies with r for a fixed (small) λ . The three characteristic efficiency regimes, FIF, Parrondo, and SIF, are clearly exhibited. Data points represent numerical averages over 100 simulations, and solid curves show the theoretical predictions from Eq. (7).

(2) *SIF (slow is fast)*. When $p_o = 0$, counterintuitively, routing all agents via TSP worsens congestion, while GSP dominates, illustrating that “slower” choices can yield faster collective outcomes.

(3) *Parrondo’s paradox*. When $0 < p_o < 1$, a clever mix of TSP and GSP yields better performance than either pure strategy—an emergent effect reminiscent of Parrondo’s paradox, where alternating individually disadvantageous strategies leads to a favorable result.

Results. Equation (9) indicates that, besides the network structure itself, both the traffic level r and the congestion sensitivity λ are crucial in determining the critical routing preference p_c and, consequently, the optimal system efficiency. To verify this prediction, we conduct the numerical experiments to get the average travel time $\langle T \rangle_p$ as a function of p for different (r, λ) combinations (Fig. 3). Three characteristic regimes appear: a monotonic decrease of $\langle T \rangle_p$ with p , corresponding to the FIF regime; a nonmonotonic (U-shaped) dependence, signaling the Parrondo regime; and a monotonic increase with p , indicative of the SIF regime. This behavior arises from the trade-off between intrinsic and congestion-induced delays. While TSP minimizes the intrinsic travel time for individual agents, it tends to concentrate traffic on links with short τ_0^e , thereby amplifying congestion delays. From a system-wide perspective, such “selfish” routing can reduce overall efficiency. As either r or λ grows, the congestion costs outweigh intrinsic-time benefits, driving a transition from FIF (where TSP is globally optimal) to SIF (where GSP becomes preferable), with an intermediate Parrondo regime in which mixing the two strategies achieves the best performance.

To identify the optimal routing strategy under varying traffic conditions, we determine the value of p that maximizes

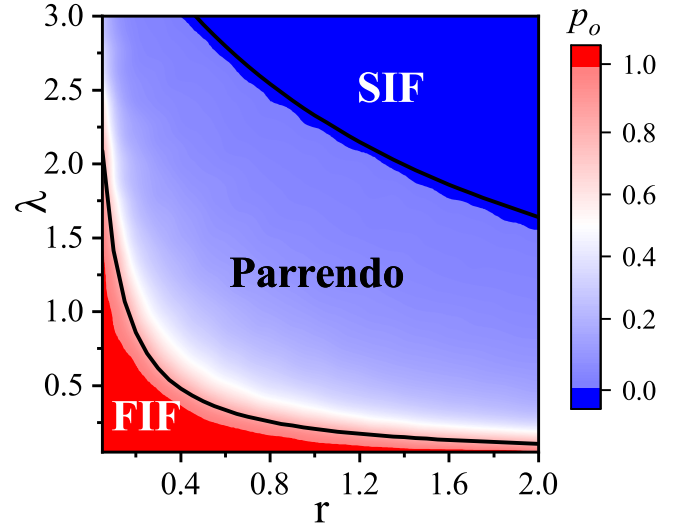


FIG. 4. Phase diagram of traffic efficiency in the (r, λ) parameter space. Each colored point represents the optimal routing preference p_o obtained from numerical simulations across 40×60 combinations of traffic level r and congestion sensitivity λ . The color indicates the value of p_o : blue for $p_o = 0$ (SIF regime), a color gradient for $0 < p_o < 1$ (Parrondo regime), and red for $p_o = 1$ (FIF regime). Solid curves denote the theoretical phase boundaries predicted by Eqs. (11) and (12).

efficiency for a given traffic level r and congestion sensitivity λ . This requires delineating the parameter regions associated with the three regimes—FIF, Parrondo, and SIF. Theoretically, the regime boundaries in the (r, λ) plane follow from Eq. (9) together with the piecewise definition of p_o in Eq. (10), yielding the critical conditions

$$\lambda_c^0 = \frac{(1 - N) \langle \tau_0^e \Delta b^e \rangle_e}{\langle (2rb^{G,e} + N - 1) \Delta b^e \rangle_e}, \quad (11)$$

$$\lambda_c^1 = \frac{(1 - N) \langle \tau_0^e \Delta b^e \rangle_e}{\langle (2rb^{T,e} + N - 1) \Delta b^e \rangle_e}. \quad (12)$$

For fixed r , the system exhibits FIF when $\lambda \leq \lambda_c^0$, Parrondo when $\lambda_c^0 < \lambda < \lambda_c^1$, and SIF when $\lambda \geq \lambda_c^1$.

Figure 4 shows the optimal preference p_o across (r, λ) obtained from simulations. For each parameter pair, we performed 100 runs for every $p \in [0, 1]$ and identified the value minimizing $\langle T \rangle_p$. The resulting phase diagram reveals three distinct regions, color-coded as follows: red for FIF, a gradient for Parrondo, and blue for SIF. At low r and λ (lower left), link flows remain light and congestion negligible. Here, the inherent travel time savings from TSP dominate, leading to the FIF regime. At high r and λ (upper right), the SIF regime appears, where even limited TSP usage overloads short links, incurring substantial delays. In this scenario, GSP, which uses fewer links and avoids congestion, outperforms TSP, defining the SIF regime. Between these extremes lies the Parrondo regime, where a judicious mix of TSP and GSP balances the competing effects of intrinsic-time savings and congestion avoidance.

The theoretical phase boundaries derived from Eqs. (11) and (12) accurately delineate these three dynamical regimes. Sustaining FIF as r grows requires progressively smaller λ , a

desirable regime that aligns individual incentives with system-wide efficiency. Conversely, under high traffic demand, even moderate congestion sensitivity drives the system into SIF, leading to inefficient performance that is difficult to mitigate. The Parrondo regime reflects a regime of strategic interplay among agents, necessitating system-level coordination or optimization to harness the collective gains of hybrid routing. The ability to predict these transitions theoretically provides valuable guidance for traffic management and route-planning strategies, offering a pathway to improved transport efficiency.

We have employed heterogeneous scale-free networks to demonstrate the analytical approach within a non-Markovian traffic dynamics setting and expose the associated efficiency transitions. To establish generality, we extended the analysis in the Supplemental Material [27] to consider additional system parameters, including the inherent travel-time heterogeneity (controlled by $\bar{\tau}_0$) and network connectivity (varied via $\langle k \rangle$), as well as homogeneous Erdős-Rényi random networks. In all cases, the same qualitative phenomena, FIF, Parrondo, and SIF, are observed, underscoring the robustness of our findings.

Conclusion. In this study, we introduce a parsimonious yet physically grounded non-Markovian traffic model that explicitly incorporates congestion delays arising from simultaneous link usage. By analyzing system-wide efficiency under two canonical routing strategies, time shortest path and geographically shortest path, we derived a closed-form

expression for the average travel time as a function of routing preference p . Our theory reveals three distinct phases of efficiency (FIF, Parrondo, and SIF), with analytic conditions specifying their emergence in terms of key network and traffic parameters. Simulations across diverse topologies and parameter regimes confirm these predictions. The underlying mechanism stems from load imbalance induced by heterogeneous inherent travel times: Links with shorter inherent times attract disproportionate traffic flow, amplifying congestion and paradoxically producing longer actual travel times. Strikingly, this imbalance gives rise to two counter-intuitive phenomena: a “slow-is-fast” effect, where detouring through longer paths improves collective performance, and a Parrondo-like regime, where mixing two individually suboptimal strategies yields the best outcome. By capturing this effect within a minimal framework, our model provides actionable insights for controlling and optimizing transport efficiency in real infrastructures. The results also suggest principles for designing routing algorithms and flow-allocation strategies in communication, logistics, and urban mobility systems.

Acknowledgments. The research was supported by the Natural Science Foundation of Anhui Province in China under Grant No. 2508085QF248 and the National Natural Science Foundation of China under Grant No. 12072340.

Data availability The data that support the findings of this article are not publicly available. The data are available from the authors upon reasonable request.

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