2024 Tenth Indian Control Conference (ICC)
9 - 11 December, 2024
IISER Bhopal, India

Beyond the First Delay: Modeling Knock-On Effects

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***Abstract*—Urban transportation networks often encounter delays that cascade as secondary disruptions throughout the system. While delay prediction using historical or simulated data is well-established, there remains a gap in accurately forecasting secondary delays propagated through interconnected services within the network without relying on periodicity assumptions. In this paper, we introduce a secondary delay propagation algorithm for suburban operations within a division of Indian Railways. Under the assumption of a static timetable and fixed network topology, this algorithm effectively predicts future delays based on initial primary delays. Additionally, we introduce the concept of systemic stress and examine its redistribution in the presence of secondary delays. We demonstrate resilience as the ratio of recovered services to affected services and rapidity as the time required for the network to return to its regular schedule. Finally, we conclude with the framework's potential to predict dynamic freight corridors in real-time, enabling railway companies to operate unscheduled, profitable freight services without disrupting passenger operations.**

Keywords: Delay Propagation, Urban Transportation Network, Event Graph, Network Stress

I. Introduction

Timetabled urban transportation networks are essential to modern cities. Designing these timetables requires meticulous planning, as detailed by Cacchiani et al. [1] for railways and Ibarra et al. [2] for buses. A primary focus of these planning efforts is ensuring punctuality [3] and stability [4]. Comprehensive overviews of reliability in public transportation services are provided by Vromans et al. [5] and Kathuria et al. [6]. However, various unavoidable external factors still affect these networks leading to secondary delays or knock-on effects [7], [8], which significantly disrupt service quality and operational efficiency [9]. In such dynamic systems, network controllers are tasked with making real-time control decisions such as adjusting train dispatch times, reallocating platforms, or rearranging service precedence to maintain network stability and minimize disruptions. However, often at times, the impact of such decisions are not known a-priori and are only found out post execution, which may prove detrimental to the network. This underscores the importance of understanding systemic stresses and timetable resilience to external delays, as discussed in [10] and [11]. Addressing these challenges involves analyzing existing timetables [12], designing more robust schedules [1], implementing real-time control measures [13], and enhancing the network's ability to recover from disruptions [14]. These strategies provide invaluable insights for the operations managers, enabling them to take appropriate actions during disruptions. Further discussion on these topics can be found in Pender et al. [15]. Various factors, often antagonistic, play a crucial role in establishing a timetable: increasing frequency may increase redundancy and reliability, but in an over-stressed network, reliability may significantly drop due to insufficient headway for recovery [16]. Indian Railways runs the remunerative and unscheduled freight services [17] within 'freight corridors', which are spatial-temporal gaps between the unremunerative and scheduled passenger services [18], thereby making the revenue flow sensitive to timetable disruptions. Delayed passenger services can obliterate established freight corridors on one hand and dynamically generate newer ones due to the redistributed schedules which are crucial to predict beforehand, so that crew and locomotives can be arranged in time. For more details on operations planning in Indian Railways, the interested reader is directed to [19]. In this paper, we aim to predict secondary delays in large-scale urban transportation networks with established timetables.

II. Literature Review

Traditionally, LSTM-based models and recently, Graph Neural Networks and Attention-based models have been used to predict delays in such networks, using simulated/historical data. LSTM-based delay prediction is proposed in [20] whereas in [21] a Spatial-Temporal Graph Convolution (STGCN) is proposed utilizing the spatial temporal structure of the network. However, in [22], it is pointed out that STGCN suffers from the inability to handle long sequences and hence proposes Spatial-Temporal bidirectional LSTM (ST-BiLSTM) to predict delays. In [23] delay propagation in flight networks depending on different network topologies is simulated, whereas in [24], the authors propose delay prediction with agent-based passenger simulation. Convolutional Neural Network-LSTM (CNN-LSTM) is used to predict secondary flight delays with convolutional Block Attention Mechanism in [25]. [26] provides a detailed explanation of the suitability of using RNNs to predict knock-on effects in railway networks. [27] takes a different approach from the explainability perspective to 'discern' the reasons behind delays. Tiong et al. [28] provides an in depth review

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of various delay prediction methods. Secondary delays are generated when primary delays spread through the network, affecting other services and routes. In [29] secondary delays are defined as the ones "that occur when the train needs to wait to move to its next infrastructure element, which is currently at full capacity".

Whereas extensive literature exists on stochastic delay prediction in railway networks based on empirical data, the corpus is prohibitively scarce with respect to ex-ante deterministic delay prediction based purely on the designed timetable and network topology. Two related works in this domain are by Rob M.P. Goverde in [30] and [8], which compute the dissemination of delays over a timetable using max-plus algebra. Two significant assumptions in this method are the periodic and acyclic timetable, which may not always be true in some suburban railway networks. Understanding how a network acts as a catalyst for delay propagation is essential because network controllers act as feedback agents, continuously adjusting operations in response to real-time disruptions. Their decisions, based on immediate feedback, aim to mitigate delays, stabilize the system, and minimize cascading effects, ensuring efficient network performance. If a network comprises N events (arrivals and departures), then the delay $\mathbf{D}_t$ at time t can be considered as a N-dimensional vector, $\{\epsilon_t^1, \epsilon_t^2, ..., \epsilon_t^N\}$, where each component denotes the delay of that event at time t. If $\mathbf{D}_t$ is the initial delay at time $t = t$, then our objective is to derive $\mathbf{D}_{t+1}$ from $\mathbf{D}_t$. More formally, we establish the algorithm that characterizes the chain:

$$\{\epsilon_t^1, ..., \epsilon_t^N\} \rightarrow \{\epsilon_{t+1}^1, ..., \epsilon_{t+1}^N\}$$

given the primitives: timetable TT, rakelink RL and network NW. Once the delays in the next time step are ascertained they can serve as the input to derive the secondary delays at the next timestep and so on until the delay vector becomes identically zero, i.e., $\mathbf{D}_t = \mathbf{0}$ where bold 0 indicates component-wise 0-vector. Our paper proposes a similar approach to [30] but without the assumption of a periodic timetable. The only assumption in our method is the mere existence of a timetable and a rake link. Our model is set apart due to its exact prediction mechanism relying on the three primitives, without any other constraints, by utilizing the sparse nature of the event graph (to be explained later). Thus, it poses tremendous potential for real-time to near-real-time applications as a ideal control mechanism with feedback loops helping operations managers to foresee and enact impactful decisions. Finally, an interested reader is directed to [31], [32], [33], [34] for further details on delay prediction literature.

III. Data and Methodology

A. Primary Data

Our study network is Sealdah division, one of the divisions of Indian Railways, with a total track km of 1752.83km, catering to 212 stations through 887 suburban services (apart from the mainline services). For the sake of simplicity, in this paper, the entire study network is assumed to comprise only the suburban services operated under Absolute Block Signalling [35] and all stations are considered as block stations. These simplifying assumptions only make the data preparation stages easier without affecting the logic of the model. The three primary data required in this study are timetable, rake-link, and network topology. Table I shows one row of a sample timetable: 'sid' is the service id that arrives at 'stn' at 'sch_arr' and departs at 'sch_dep'.

TABLE I
One row from a sample timetable

sid	station	sch_arr	sch_dep
33411	BLN	10:30	10:31

Table II shows a row from a sample rakelink: rid is the rake id that caters to service 33412 after completion of 33411, with a layover of 900s. So if 33411 is beyond 900s late to arrive at its final destination, then it will affect the departure of 33412 from its origin.

TABLE II
One row from a sample rakelink

rid	sid	next_sid	layover
N23	33411	33412	900

These primary data are used to create an event graph as follows.

B. Data Preparation

An event is defined as the arrival or departure of a train (the term 'train' and 'service' are interchangeable) from a station. Goverde discusses a similar concept of a timed event graph but with different node attributes in [30]. Our event graph is a directed graph G prepared by assuming all arrival and departure events as nodes and their dependencies as edges:

1) Preparation of Nodes: In the event graph, an event is minimally identified by the following attributes: *event_type*, *sid*, *route*, *time*, *runtime*, *time-tabled speed*, *maximum permissible speed*, *maximum reduction*. The attributes are best explained through an example event: Train 33741 (*sid*=33741) departs (*event_type*='dep') from station 'BNJ', along the route 'BNJ-BNAA' (*route*='BNJ-BNAA' is an ordered pair of stations) and takes 5 minutes (*runtime*=300) to reach its next stoppage at a distance of 5 km, which means the average time tabled speed is 60kmph (*time-tabled speed*=60). Although a node seems to depict a point event (like arrival or departure), by virtue of the runtime attribute, it also has an 'activity' like characteristic. The maximum permissible speed of the section may be 100kmph. This means that the train can reach a mean speed higher than the time-tabled speed of 60kmph, but not so high so that the top speed overshoots the speed restriction. For simplicity, the highest achievable speed is set to *minimum(1.2*time-tabled speed,90)*. These are hyper-parameters and can be adjusted depending on the situation. In this study, it is assumed without loss of generality that

a delayed train tries to make up for lost time by speeding up. Traveling at a greater speed implies the travel duration will reduce; hence the maximum achievable speed imposes a limit on the maximum amount by which the travel duration can be reduced (to ensure speed restrictions). In the specific case, this comes out to 120s (*maximum reduction=120*).

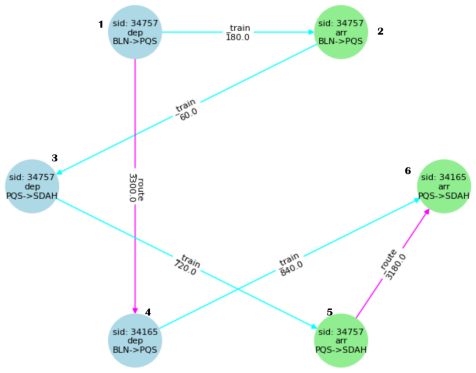


Fig. 1. Sample subgraph, showing nodes and edges with different keys (link type edge is not shown)

2) Preparation of Edges: Two nodes are connected if a delay of the parent event can affect the start time of the child event. Each edge has two attributes: *key* and *weight*. The **weight** attribute denotes the headway from the parent to the child event. The **key** attribute qualifies the relationship between the parent and child nodes: if both pertain to the same 'sid', then *key='train'*, if both pertain to the same 'route', then *key='route'* and if both are different (meaning rake-linked services) then *key='link'*. Fig.1 shows a sample subgraph of the actual event graph under study. Node 1 can be delayed at most by 180s before it will start affecting the child node 2. Delaying node 1 beyond 3300s will also affect node 4. The overflow above these values will be the amount by which the child nodes will be delayed.

Edge weights, w_{uv}, are added to the edges based on the time differences between parent and child events. If *key='train'*, then w_{uv} represents the slack/recovery time and can be adjusted to a small positive number if required, and even be set to specific values for each individual edge depending on the individual slack/recovery times of the corresponding event. For this study it is taken to be 0. If *key='link'*, then $w_{uv} = l$ where l is the layover between the connected services. This results in an event graph with 29104 nodes and 57238 edges.

C. Methodology

Here we propose a delay propagation algorithm, followed up by a method to calculate stress, resilience and rapidity during disruptions.

1) Delay Propagation: Let u represent the current node and v one of its successors, with d_u and d_v being their respective current delays. The edge weight for the edge from u to v be $w_{u,v}$ and m_v be the maximum allowable reduction in runtime for node v and α be the decay rate of propagated delay, indicating that a train tries to make up for lost time by speeding up. Let also δ_{ms} represent the minimum stoppage time, in seconds, ensuring passengers to alight/board safely, The delay propagated from node u to node v is:

- If u and v correspond to the arrival and departure of a train at a station:

$$d_v \leftarrow \max\left(d_v, d_v - w_{u,v} - \min\left(\alpha \cdot d_u, m_v, \delta_{ms}\right)\right)$$

- Otherwise:

$$d_v \leftarrow \max\left(d_v, d_v - w_{u,v} - \min\left(\alpha \cdot d_u, m_v\right)\right)$$

Algorithm 1 Delay Propagation

Require: Current node u, successor node v, delays d_u, d_v, edge weight $w_{u,v}$, max reduction m_v, min stop time δ_{ms}, decay rate α

Ensure: Updated delay d_v

1: **if** u and v denote the arrival and departure of the same/linked from a station **then**
2: $\quad d_v = \max\left(d_v, d_v - w_{u,v} - \min\left(\alpha \cdot d_u, m_v, \delta_{ms}\right)\right)$
3: **else**
4: $\quad d_v = \max\left(d_v, d_v - w_{u,v} - \min\left(\alpha \cdot d_u, m_v\right)\right)$
5: **end if**

The algorithm begins by initializing a priority queue with all initially delayed nodes and their corresponding delays. It processes each node u, determining the effect of its delay d_u on successor nodes v. If u and v represent the arrival and departure of the same/linked train, v's delay is updated as: $d_v \leftarrow \max\left(d_v, d_v - w_{u,v} - \min\left(\alpha \cdot d_u, m_v, \delta_{ms}\right)\right)$, where $\alpha \cdot d_u$ is the scaled delay at u, m_v is the maximum allowable reduction at v, δ_{ms} is the minimum stoppage time, and $w_{u,v}$ is the edge weight. If u and v do not represent arrival and departure of the same/linked train, δ_{ms} is ignored. Whenever v's delay is updated, it is added to the priority queue. The max operator ensures that the delays either increase from the current delay or remain unchanged and the min operator takes care of the constraints. This process continues until the queue is empty, ensuring that no residual delay remains to be propagated through the network. Additionally a path list is maintained for book-keeping purpose, for each delayed node, that tracks the path along which the current delay was propagated.

2) Bunching and Stress Detection: Bus bunching is a widely studied phenomenon in public transit networks. Daganzo in [36] provides a detailed analysis of bus bunching, where it is defined as "the phenomenon of two or more public transport vehicles that serve the same line moving in pairs or very close to each other as a result of deviation from defined headways or published schedules". In this study we expand this definition to a more generic concept of 'Systemic Stress'. No explicit definition of systemic stress in a public transit network is found in the literature. Given the delay propagation algorithm, if the number of events within a time

interval t to $t + \Delta t$ in the delayed network is N_d, which earlier contained N_u events as per schedule, then we define systemic stress at time t, as:

$$S_t = \frac{N_d}{N_u}$$

Thus it is the relative density of events per unit time in a delayed network, compared to the un-delayed version. The definition of 'event' is kept flexible allowing to be suited to applications. An established timetable enforces a certain distribution of event (in our case, event is arrival and departure of train services to and from stations) densities throughout the operational tenure (an operational tenure of a set of services starts from the start of the first service in the set and ends with the termination of the last service).

3) Resilience: One key performance indicator vastly used in urban transportation research, is resilience [10]. In literature, various similar definitions are available, but in general it refers to the ability of a transport system to handle unexpected disruptions and quickly bounce back to normal functioning after a disturbance. It has a temporal dimension as pointed out in [37], also called rapidity, given by the time the system takes to recover to the usual state. In this study, we propose to quantify resilience, as follows:

Suppose initially $\varepsilon_{initial}$ events are delayed which affected τ_{inital} services initially, which cascaded through the network affecting τ_{peak} services en route, during various times of the day. However, the services tried to make up for lost time, as much as possible ($\alpha = 1$), without violating the speed constraints and finally τ_{final} services remained delayed while reaching their final destination. Then we propose:

$$resilience = (\tau_{peak} - \tau_{final})/\tau_{peak}$$

When disrupted, typically any network goes through a phase called the resilience triangle as depicted in Figure 2, which is taken from [38] We quantitatively illustrate the resilience

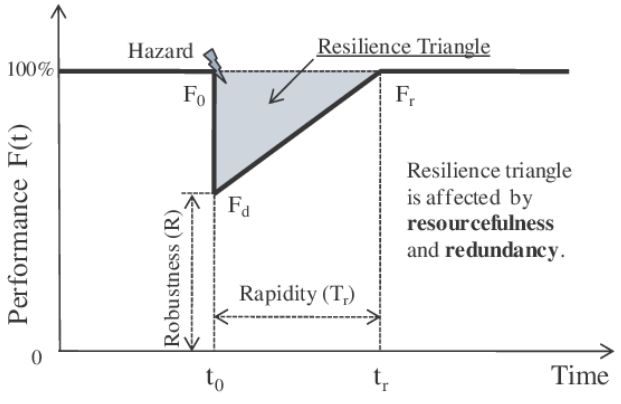


Fig. 2. Resilience Triangle

triangle as follows: The secondary delays are first calculated using a delay propagation algorithm. If an event E, originally scheduled to occur at time t_E, is delayed by Δt_E seconds, then for the duration from t_E to $t_E + \Delta t_E$, the event experiences a sequence of delays: $(\Delta t_E, \Delta t_E - 1, \ldots, 0)$. This delay is assigned to each delayed event, and the total number of delayed events per second is computed during the entire delay period.

For an event E, the delay at time t is given by:

$$D_E(t) = \begin{cases} \Delta t_E - (t - t_E) & \text{if } t_E \leq t < t_E + \Delta t_E, \\ 0 & \text{otherwise.} \end{cases}$$

The total number of delayed events at time t is:

$$N(t) = \sum_{E \in \mathcal{E}} D_E(t)$$

where $\mathcal{E}$ is the set of all events.

Finally, *rapidity* is defined as the time it takes for all services and hence the entire network to return to normal schedule.

IV. Results

A. Delay Propagation:

We randomly delayed all of the 80 scheduled events within 17:40-17:41 of 24nd Sept, 2024, by random amounts ranging from 10-20mins. We set $\alpha = 1$, indicatying the trains try to

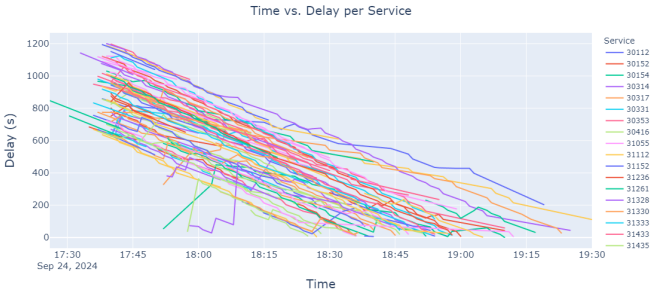


Fig. 3. Secondary delays suffered by various services from 17:40:00 till 19:31:51 (all 90 affected services are not listed due to lack of space)

make up for lost time by speeding up as much as possible while maintaining speed constraints. Fig.3 shows the delay suffered by various services: 90 services were affected in total, out of which 59 services remained delayed till they reached their final destination, but 31 services recovered en-route.

B. Stress

We took the density of events per minute established by the original timetable as the baseline. For every minute the systemic stress is plotted against the time of day. Fig.4 shows the redistribution of stress due to secondary delays. In this example, 200 random events throughout the day, pertaining to 176 services were delayed by various amounts ranging from 10-20mins and this displaced 6842 events pertaining to 410

services, some of them being pushed into the next date, as is evident from the figure. $stress < 1$ signifies reduced stress, because some events have been delayed, whereas $stress > 1$ denotes 'bunching' of events. Stress as high as 4 can be observed in the resultant plot.

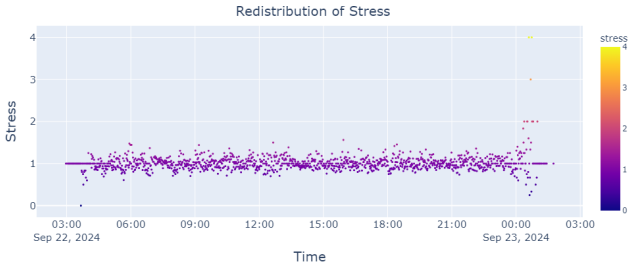


Fig. 4. Redistribution of stress

C. Resilience

We disrupted all 90 events occurring/continuing within 9:30am to 9:31am on 24nd Sept, 2024, by random amounts ranging from 10-20mins and their secondary effects are ascertained through the delay propagation algorithm. This resulted in $\tau_{initial}$ = 80, τ_{peak} = 110 and τ_{final}= 74, meaning $\tau_{peak} - \tau_{final}$ = 36 services recovered fully, giving us a resilience of $\frac{\tau_{peak}-\tau_{final}}{\tau_{peak}}$ = 0.33. The secondary delays lasted till 11:16:09, hence the rapidity is 1hr 46m 9s.

In order to illustrate the resilience triangle, we associated each event with a delay amount and counted the number of delayed events per second. Figure 5 shows the number of delayed events in y-axis and time in x-axis.

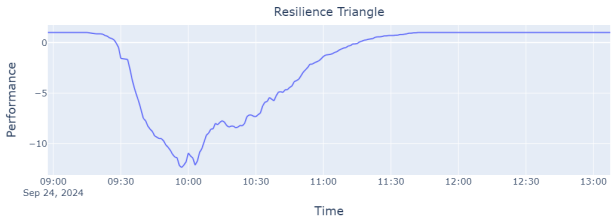


Fig. 5. Resilience triangle. Negative y-axis indicates displaced events

The initial gap in Figure 5 is due to the rolling average taken across a window of size 100 to smoothen the curve. The semblance to the Figure 2 is well visible.

V. Conclusion

In this work we have proposed secondary delay propagation in timetabled urban networks and quantified the resilience of the network under different disruptions, constrained under immutable primitives. We have also established the concept of systemic stress and its relation to the often observed phenomenon of 'bunching'. Finally, we have corroborated the existence of the resilience triangle.

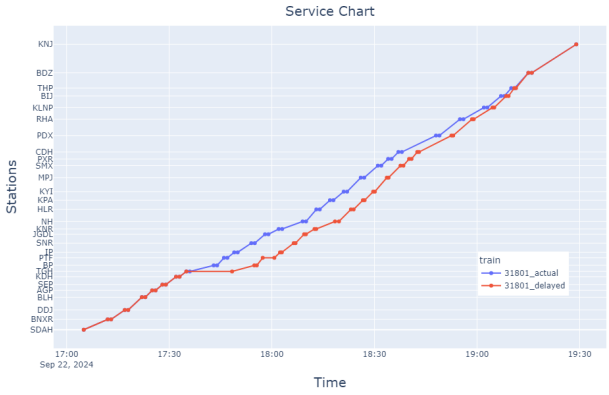


Fig. 6. Actual schedule (blue line) vis-a-vis delayed schedule (red line) of Train 31801

One significant future area of work is the real-time prediction of dynamic freight corridors arising out of delayed passenger services. The newly created corridor can be seen in Figure 6 as the space between the red and blue lines. A Railway company can decide to salvage this new corridor to run a freight service from TGH to THP, thereby earning revenue and yet not affecting any passenger service. To our knowledge, no such mechanism exists that can predict dynamic freight corridors in real time and this is a promising future direction based on this research. We also aim to develop causal estimation of secondary delays in a network: reverse engineering from empirically observed delays to estimation of initial delays is a formidable task, as explained in [39]. Suppose the network delay at each instant of time is represented as a chain as follows:

$$\mathbf{D}_t(\neq \mathbf{0}) \rightarrow \mathbf{D}_{t+1} \rightarrow \mathbf{D}_{t+2} \rightarrow \ldots \rightarrow \mathbf{D}_{t+k}(= \mathbf{0})$$

Hence an observed delay $\mathbf{D}_i$ could have arisen from any of its predecessors from $\mathbf{D}_{i-1}$ to $\mathbf{D}_0$ and propagated to the observed instant. One limitation of this study is that dynamic timetable adjustment by network controllers as a real-time delay mitigation strategy is not considered here.

In the future, we also intend to develop a railway operations Digital Twin to help network controllers in real-time decision making through analysis of decision foresight. In real time operations, networks are affected by various external and internal factors and it is difficult if not impossible to sense every factor beforehand. Hence controllers often have to rely on feedback from the network, in the form of delayed events, to take corrective actions and try to bring back the network to regular course. The number of corrective actions may vary widely and hence foresight of the impact of a decision on the network is crucial to aid in the process and this is where this work aims to help. This research is funded by the SPRING GX project under University of Tokyo.

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