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Spectral Analysis of Delay Propagation in Air-Rail Inter- modal Networks

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1 Introduction

2 Methodology

3 Results

- Preprocessing
- Expected delay detection
- Unexpected delay detection

4 Conclusion

Context



Competition between modes:

- Market overlapping
- Price volatility and ticketing complexities
- Passenger convenience issues

Motivation



Air-rail collaboration:

- Better Resource Utilization
- Resilience and Flexibility
- Improved Passenger Experience

Problem



Cascading delays leads to widespread operational inefficiencies, increases passenger travel times, resource bottlenecks, and degraded system reliability.

Problem

How can advanced analytical methods be developed and applied to reliably **identify, quantify, and forecast both expected and atypical disruption in intermodal transportation networks** in order to enhance operational response and network resilience?

Literature review

State-of-the-art

- Robust Optimization & Stochastic Modeling
 - Miller-Hooks, X. Zhang, and Fatourchi 2012
 - Chen and Miller-Hooks 2012
- Simulation-Based and Real-Time Decision Support
 - Burgholzer et al. 2013
 - Hrušovský et al. 2021
- Machine Learning & Predictive Analytics
 - Balster et al. 2020
 - Wang, J. Zhang, and Gu 2023
- Network Science & Complex Systems
 - Serdar, Koç, and Al-Ghamdi 2021

Spectral Methods approach

Advantages

- Supports earlier and more precise detection of atypical disruptions
- Enables targeted mitigation (e.g., resource reallocation, scheduling interventions)
- Enables the analysis of how disruptions propagation
- GSP can reveal non-local effects and complex interdependencies
- Encourages deeper multimodal data sharing/integration
- GSP can dynamically adapt to changing network structures

SESAR SIGN-AIR Project



SIGN-AIR

SIGN-AIR platform provides the means for Transport Service Providers (TSPs) (e.g., airports, airlines, railway operators etc.), to reach Data Sharing Agreements and complementary Smart Contracts with other TSPs and to manage their contractual relationships. While the SIGN-AIR platform only manages the contractual aspects through the data attributes offered by the TSPs, the TSPs will continue managing their data and that of their customers.

- EU-funded collaborative project on synergies, data sharing, and resilience in multimodal hubs
- Develop new frameworks for disruption management and predictive analytics

Project Impact

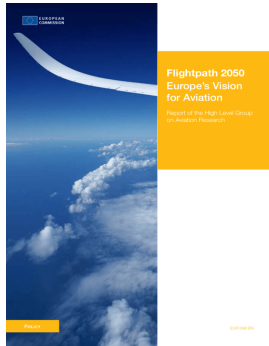


Figure: European Commission's strategic vision for aviation by 2050

- Alignment with the Flightpath 2050 vision of a seamless, multimodal, four-hour, door-to-door journey
- Alignment with SESAR's vision for next-gen multimodal mobility
- Long-term goal: Smarter, more resilient mobility for passengers

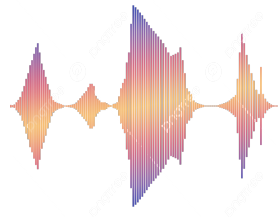
Research Objective



Analyze the delays of international hub



Detect both normal and abnormal disruption patterns



Apply Graph Signal Processing techniques

1 Introduction

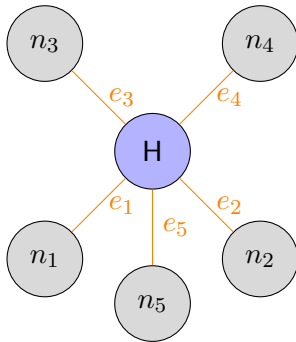
2 Methodology

3 Results

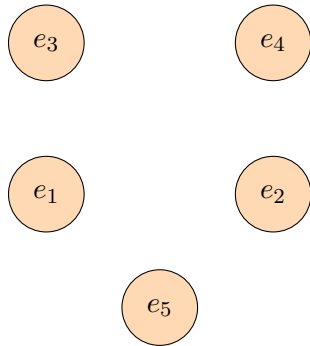
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Network Construction

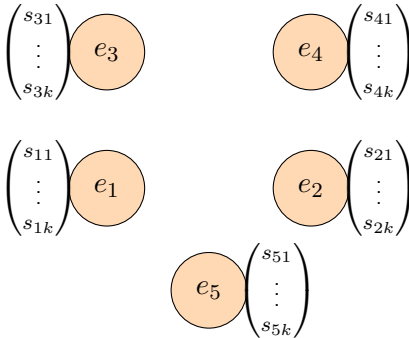


(a) Hub-and-spoke



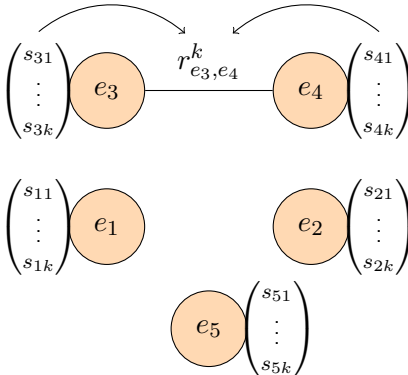
(b) Line graph

Delay network



■ Signal: Leg delay

Delay network

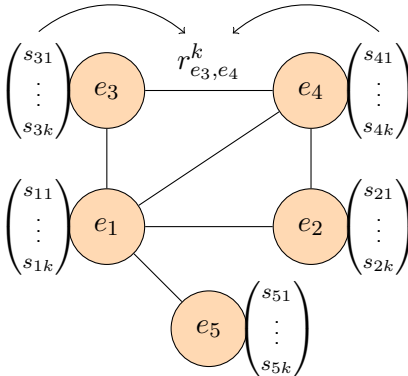


- Signal: Leg delay
- Edge weight: Pearson delay correlation

$$\rho_{e_i,e_j}^k = \frac{\sum_{l=1}^k (s_{il} - \hat{\mu}_i)(s_{jl} - \hat{\mu}_j)}{\sqrt{\sum_{l=1}^k (s_{il} - \hat{\mu}_i)^2} \cdot \sqrt{\sum_{l=1}^k (s_{jl} - \hat{\mu}_j)^2}} \quad (1)$$

$$r_{e_i,e_j}^k = \max(0, \rho_{e_i,e_j}^k) \quad (2)$$

Delay network



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$$r_{e_i,e_j}^k = \max(0, \rho_{e_i,e_j}^k) \quad (2)$$

Laplacian matrix

$$L = D - A \quad (3)$$

where

$$A = [a_{ij}] \quad (4)$$

$$D = [d_{ii}] \quad (5)$$

with

$$a_{ij} = r_{e_i, e_j}^k \quad (6)$$

$$d_{ii} = \sum_j a_{ij} \quad (7)$$

Laplacian matrix spectrum

The Laplacian L possesses a full set of orthonormal eigenvectors ν_i and eigenvalues λ_i :

$$L\nu_i = \lambda_i\nu_i \quad (8)$$

- The eigenvalues can be sorted so that $\lambda_1 \leq \dots \leq \lambda_M$.
- The corresponding eigenvectors $(\nu_1, \dots, \nu_M)$ form a basis for the signal space.

The graph Fourier transform of a graph signal s is given by $(\alpha_1, \dots, \alpha_M)$, where each α_i is computed as follows:

$$\alpha_i = s^T \nu_i \quad (9)$$

Spectral Metrics

Total Variation (TV) – Measures irregularity of delay signal
(smooth = typical; high = unexpected):

$$TV = s^T L s = \frac{1}{2} \sum_{i \neq j} a_{ij} (s_i - s_j)^2 \quad (10)$$

Total Energy (TE) – Overall delay energy distribution:

$$TE = \|s\|^2 = \sum_{i=1}^N \alpha_i^2 \quad (11)$$

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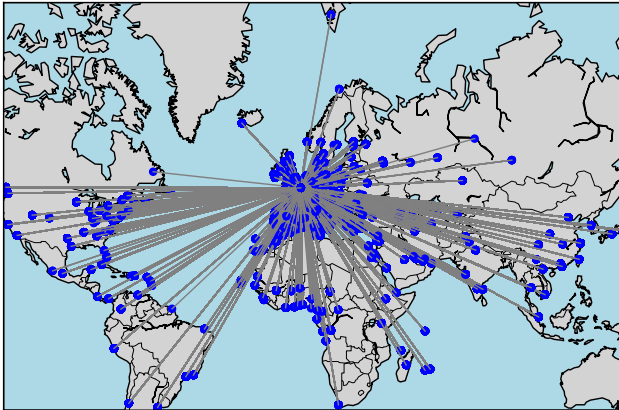
4 Conclusion

Data Sources



- Real-world flight delay data: EUROCONTROL, June 2018
- Rail data: SNCF statistics, GTFS schedules, and simulated rail delays (strike periods included)
- Network model: Nodes = legs (flight/train); Edges = delay correlations

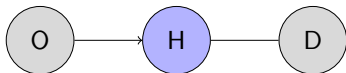
Flight network at CDG



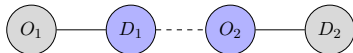
Simulated rail network

OD pair generation:

- original OD pair



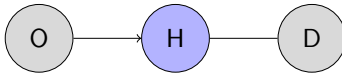
- modified OD pair



Simulated rail network

OD pair generation:

- original OD pair



- modified OD pair

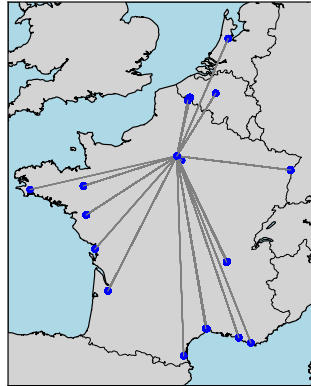
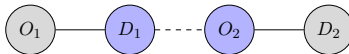
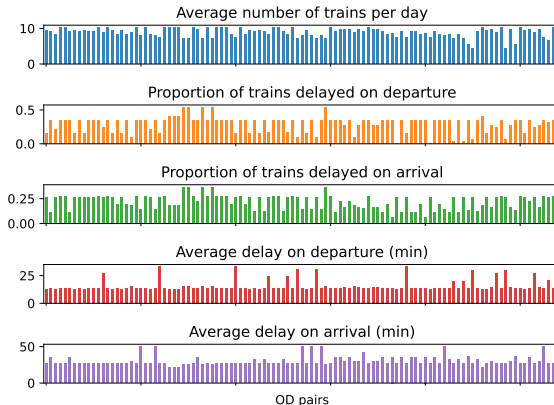


Figure: Train OD pairs passing through CDG station in June 2018.

Simulated rail network

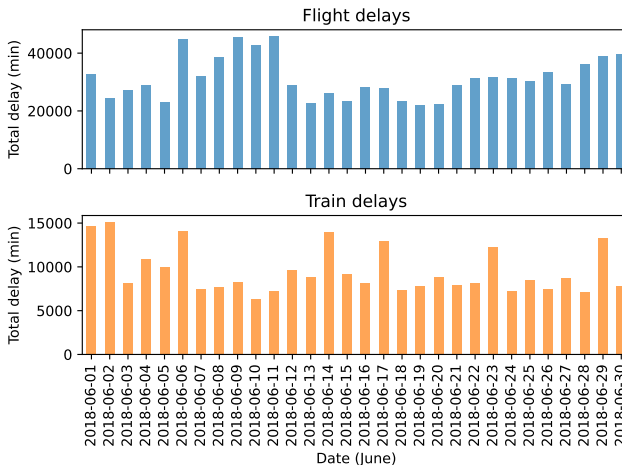


■ Daily delay modeled with exponential law

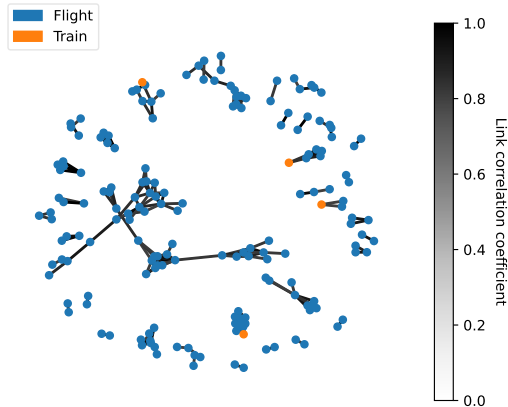
■ Strike delay modeled with uniform law

Data Processing

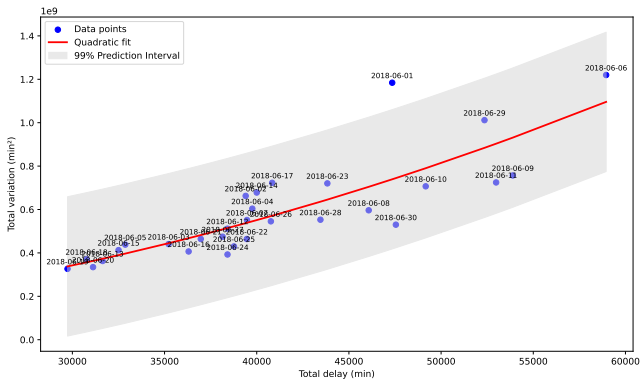
Aggregation: Delays per day, per mode



Correlation graph at CDG

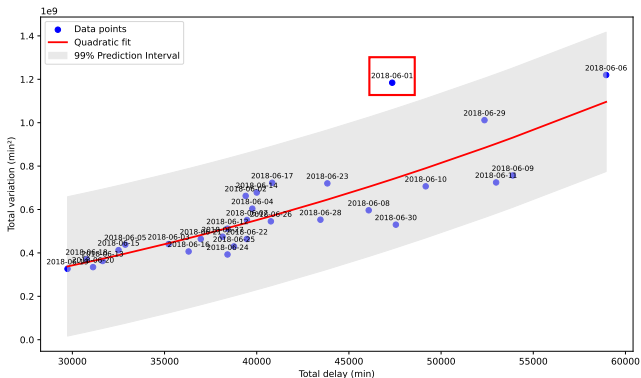


Total variation analysis at CDG



- Most of days are smooth

Total variation analysis at CDG



- Most of days are smooth
- One day is highly irregular (high TV): June 1st, 2018

Spectral Decomposition

Total Variation original formula:

$$TV = s^T L s = \frac{1}{2} \sum_{i \neq j} a_{ij} (s_i - s_j)^2 \quad (12)$$

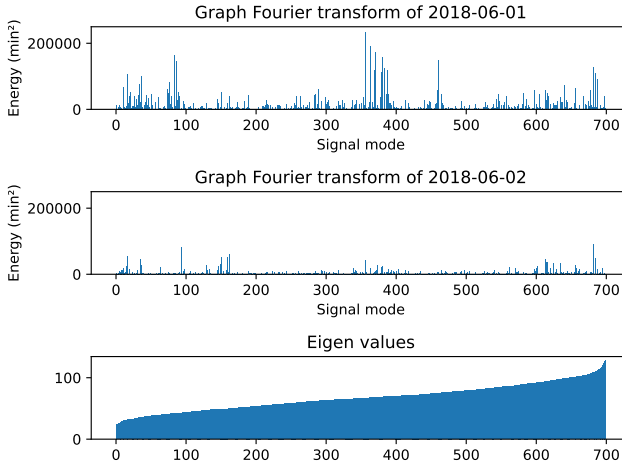
Total Variation decomposition based on signal modes:

$$TV = \sum_i \alpha_i^2 \lambda_i \quad (13)$$

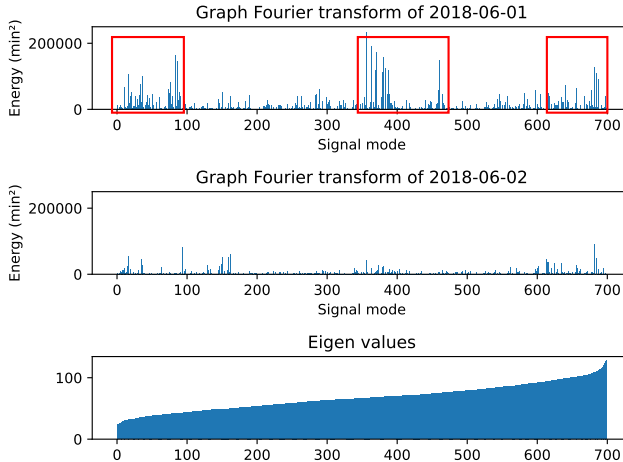
where

- λ_i is an eigenvalue of the Laplacian matrix L ;
- α_i is an mode energy of the signal s .

Spectral Decomposition



Spectral Decomposition



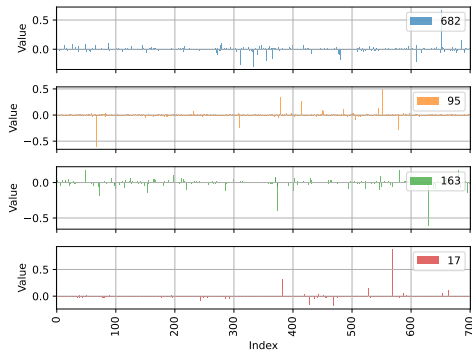
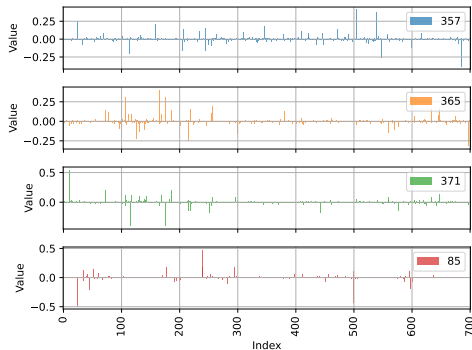
Eigenvector Energy Analysis

Table: Ranking of modes—eigenvectors of the graph Laplacian representing distinct frequency components of the delay signal—contributing most to TE on June 1 and 2, 2018.

	2018-06-01		2018-06-02	
Rank	Mode	Percentage	Mode	Percentage
1	0	16.28	0	23.47
2	357	2.42	682	2.45
3	365	1.98	95	2.23
4	371	1.78	163	1.63
5	85	1.70	17	1.49

- Mode 0 possesses the greatest proportion of the signal energy

Top Eigenvector Coordinate Analysis



- The coordinates show similar magnitudes
- The number of variations is different

Second Eigenvector Coordinates Ranking

Table: Top five absolute value of the coordinates associated to the second mode contributing the most TE.

2018-06-01			
Rank	Index	Coordinate	Leg
1	505	0.40962	('LFPG', 'SBFZ')
2	686	-0.379122	('CDG', 'Marne la Vallée')
3	539	0.3693	('LFPG', 'ZBAA')
4	548	-0.254753	('LFRB', 'LFPG')
5	24	0.243857	('DTMB', 'LFPG')

2018-06-02			
Rank	Index	Coordinate	Leg
1	651	0.673802	('UBBB', 'LFPG')
2	333	-0.297954	('LFPG', 'HAAB')
3	311	-0.261981	('LFPG', 'FNLU')
4	609	-0.212666	('LYPG', 'LFPG')
5	356	-0.189828	('LFPG', 'KMEM')

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Work summary

- GSP-based spectral analysis is powerful for revealing hidden delay propagation dynamics in hub networks
- Identifies both systemic (expected) and exceptional (unexpected) disruption patterns
- Supports smarter, more resilient, and passenger-centric multimodal operations

Perspectives

Limitations

- Data gaps, modeling assumptions (especially for simulated rail delays)
- Full validation requires richer, real-time datasets for both modes

Future Research

- Test the sensitivity of the delay models (e.g., heavy-tailed delay distributions)
- Integration with real-time data sources
- Application to other hubs and set of hubs

Thank you for your attention!

Questions?

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