

Saab – NTU Joint Lab

Variable Taxi-Out Time Prediction Using Graph Neural Networks

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Presentation Outline

- Research context and objectives
- Proposed approach
- Definitions and methodology
- Results
- Conclusions and future work

Research Context

- Airport Collaborative Decision Making (ACDM)
 - Move towards more collaborative airport environments
 - Information is shared between different stakeholders to support better decision making
- Opportunities and motivation
 - Data driven approaches
 - Complex and dynamic environment

Strategic

5 Collaborative Management of Flight Updates enhances the quality of arrival and departure information exchanges between the Network Operations and the CDM airports.

4 (CDM in) Adverse Conditions achieves collaborative management of a CDM airport during periods of predicted or unpredicted reductions of capacity.

3 (Collaborative) Pre-departure Sequence establishes an off-block sequence taking into account operators preferences and operational constraints.

2 Variable Taxi Time is the key to predictability of accurate take-off in block times especially at complex airports.

1 The Milestones Approach (Turn-Round Process) aims to achieve common situational awareness by tracking the progress of a flight from the initial planning to the take off.

Optimisation

Prediction

(Airport CDM) Information Sharing is essential in that it forms the foundation for all the other elements and must be implemented first.



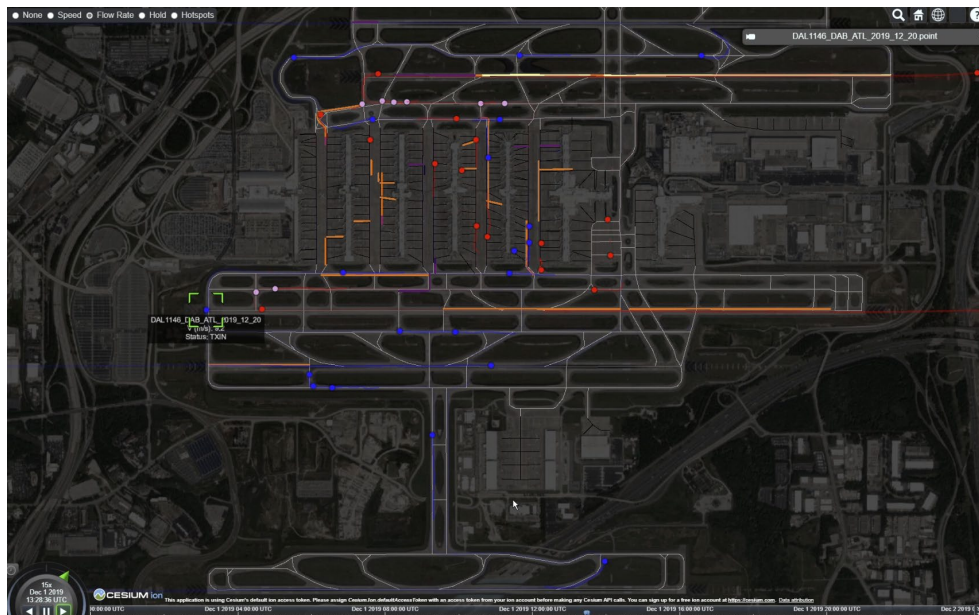
“Airport CDM Implementation Manual”, Eurocontrol (2017)

Research Objectives

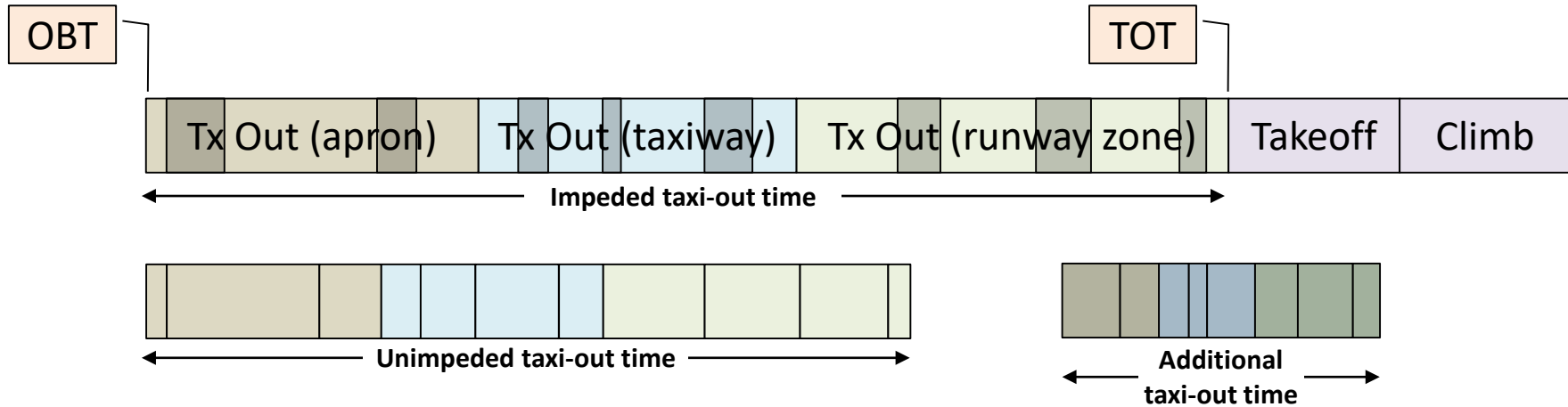
- To develop data-driven algorithms for pre-departure planning
 - Prediction/planning horizon of 30 minutes
 - Impeded taxi out time prediction
 - ❖ Using operationally available information (OBT, taxi route, queue position, etc)
 - ❖ Accounting for airport flow characteristics (arrivals + departures)
 - ❖ To an accuracy of ± 2 min for 90% for all departures
 - Pre-departure optimisation
 - ❖ Objectives: minimise overall taxi time while maintaining the predefined runway pressure
 - ❖ Decision variables: departure sequence, taxi route, Δ TSAT

Proposed Approach

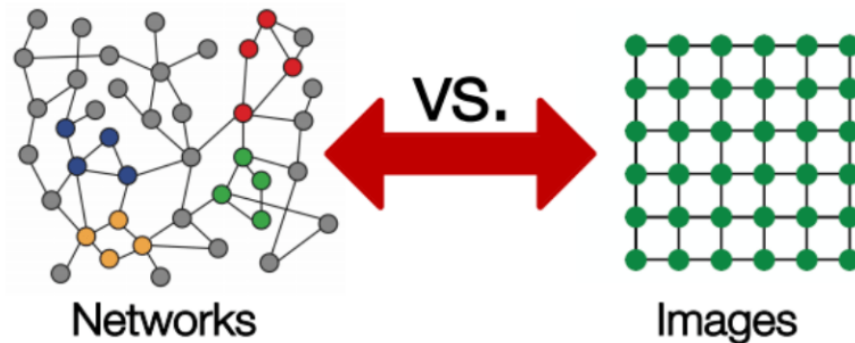
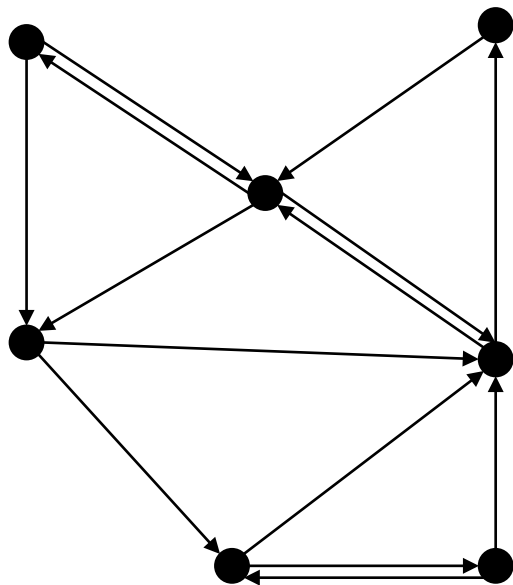
- Mesoscopic flow model
 - Movements are aggregated into flow metrics at the **taxiway level**
 - **Graph-based** approach
 - Flow information is used to predict the taxi-out times of **individual movements**
- GNN framework
 - **Deep learning** on graphs
 - Flow metrics combined with taxi route and auxiliary information



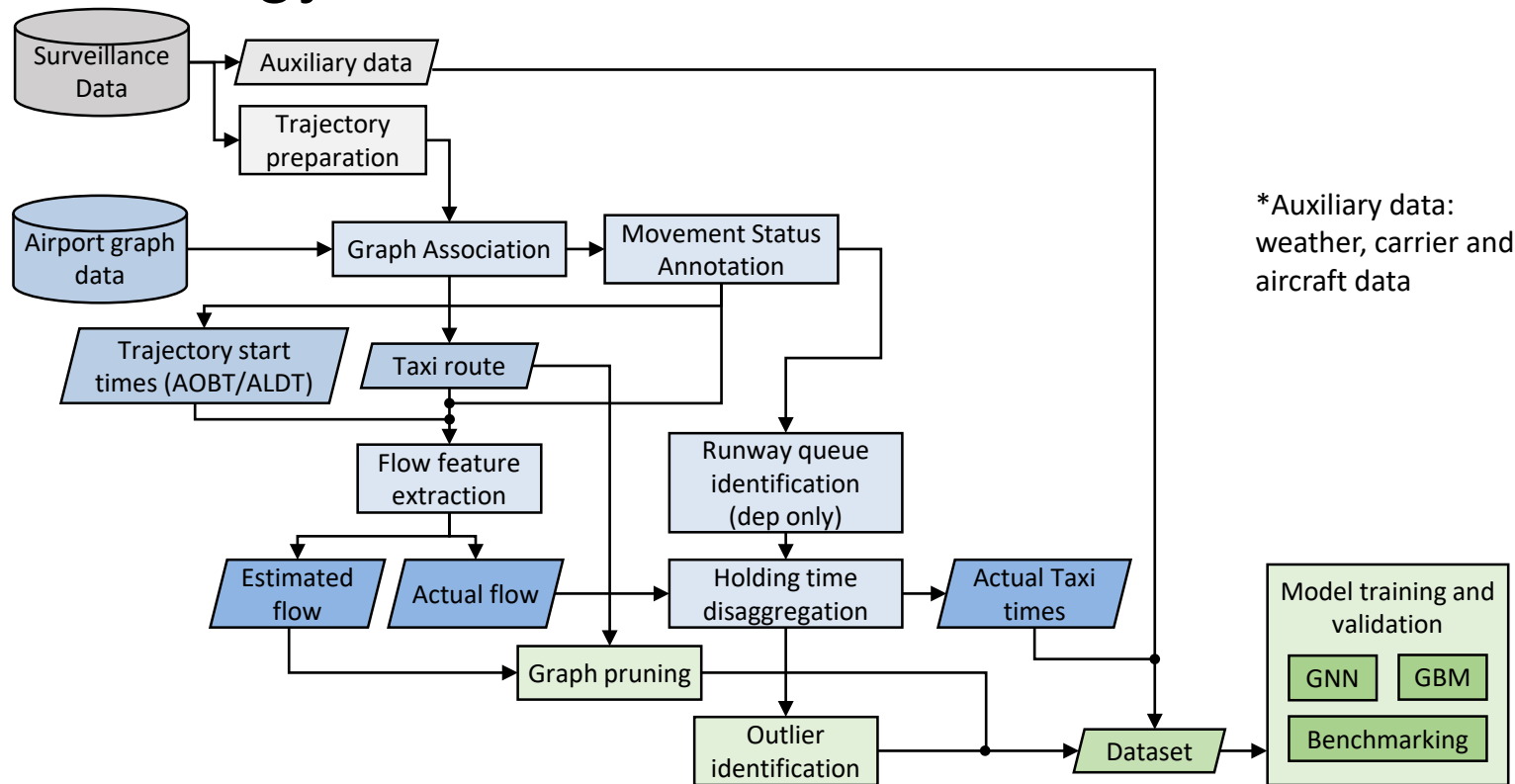
Basic definitions – taxi times



Basic definitions – graphs and GNNs

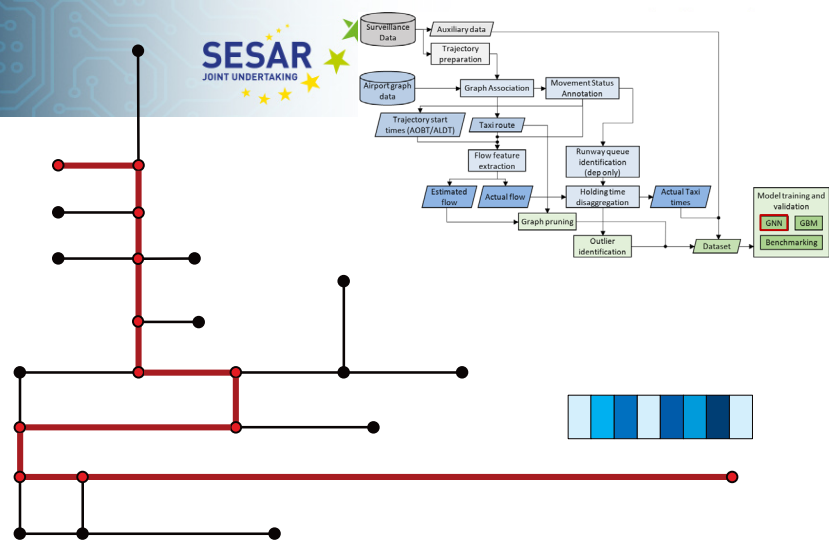


Methodology



Methodology – GNN

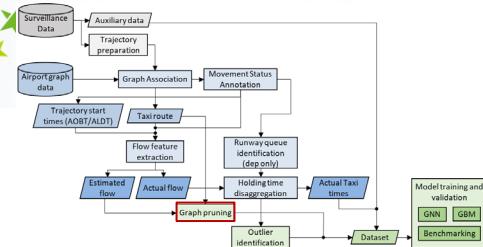
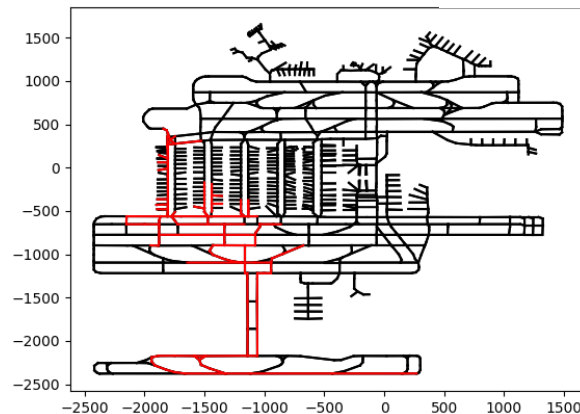
- **Graph-level** prediction task: predict the properties of a given graph
- Node attributes: **route** and **anchor** information
- Edge attributes: **topology** and **flow** information
- Global attributes: **airport-level** congestion metrics, **aircraft/airline** features, aggregate route features



Type	Attributes
Node	Intent: Node intent, Est. dist. along intent, Norm of est. dist. along intent Anchor: Node anchors, Dist. to node anchors, Anchor weights
Edge	Static: Edge type, Edge length, Inverse of edge length, Edge intent, Dynamic: Est. aircraft count along edge, Est. flow potential, Est. flow probability
Global	Queue: Queue position, Norm of queue position (divided by est. dist.) Congestion: Est. tkos/ldgs on assigned runway, Norm of est. tkos/ldgs (divided by est. time), Global ldg count, Global tko count, Global taxi in count, Global taxi out count Route: Est. route dist., Est. route unimpeded time Categorical: Airline, Wakecat, Runway ID

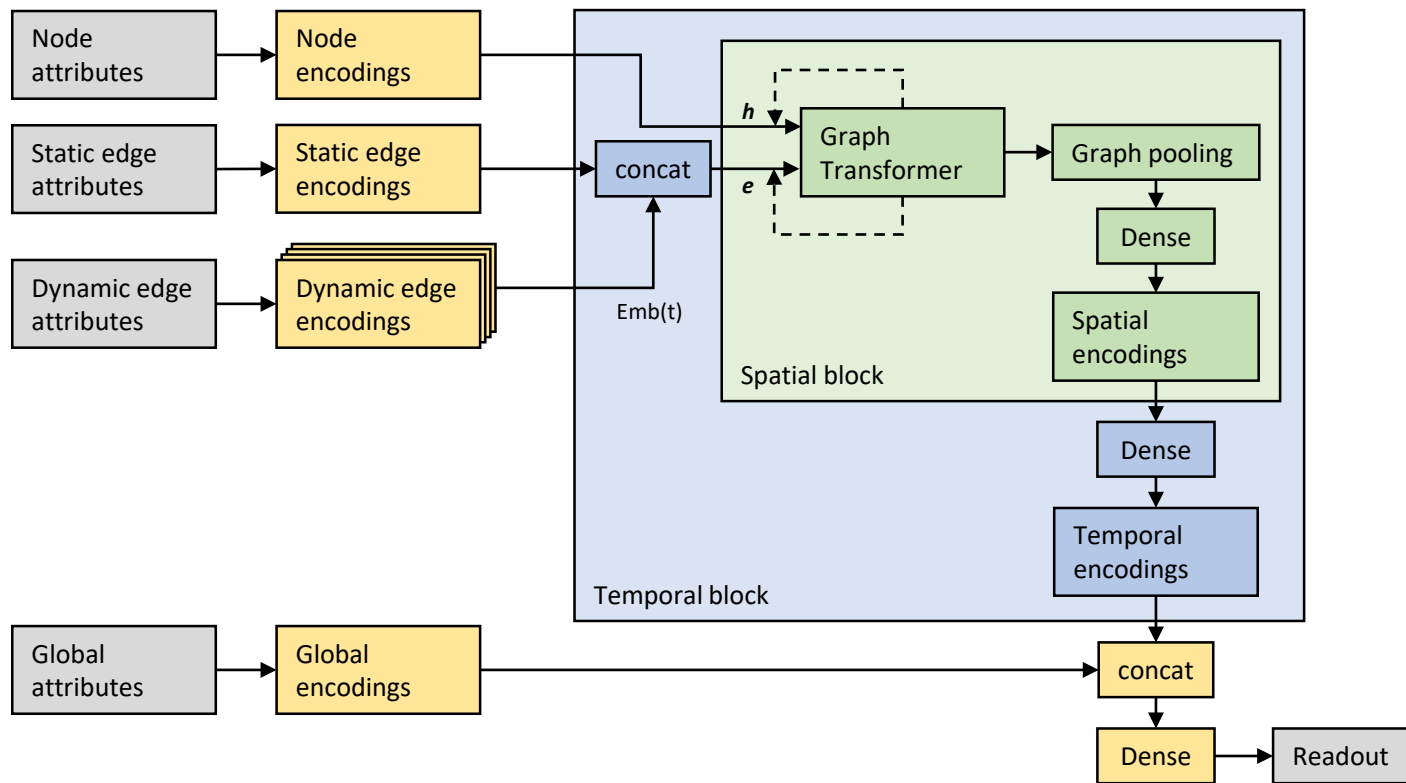
Graph Pruning

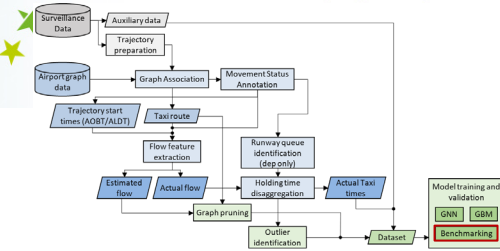
- Reduce graph size
- Pruning of nodes and edges that are distant from the taxi route
- Anchor nodes
- 2 stages of pruning
 - Distance-based
 - Flow-based



	Original		D = 500m		D = 250m		D = 200m		D = 150m	
	Node	Edge	Node	Edge	Node	Edge	Node	Edge	Node	Edge
Mean	1882	2713	208	266	112	140	85	101	81	99
Min			25	24	25	24	25	24	25	24
Max			468	712	268	397	209	291	190	269
95 prc			275	367	163	212	132	165	119	152

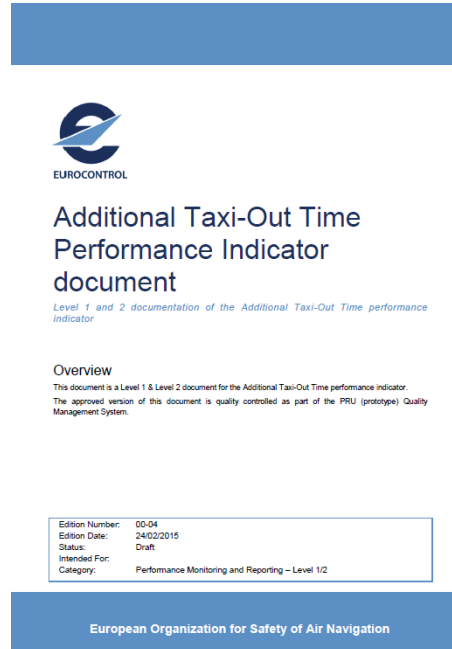
GNN Architecture





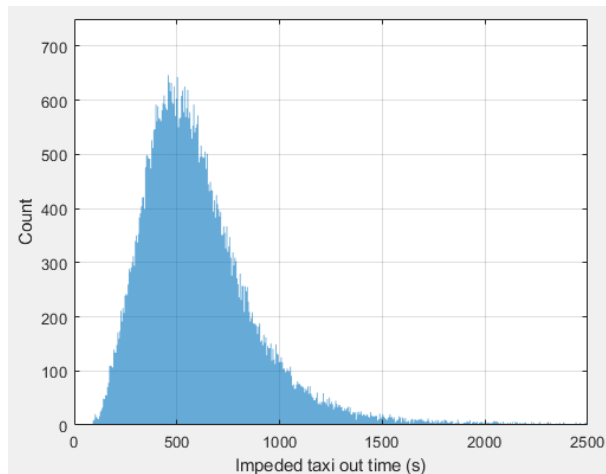
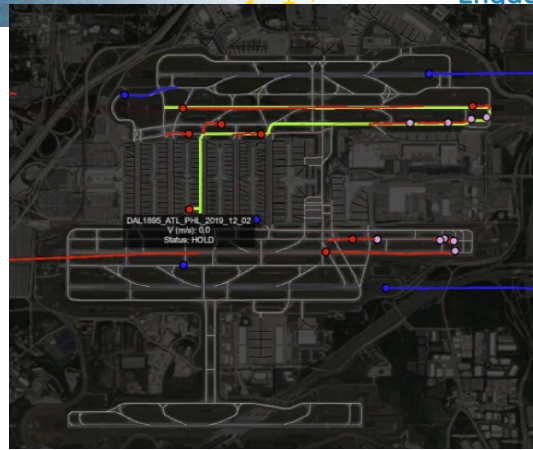
Methodology – Naïve, PRU, APO

- Besides the GNN and GBM models, we include the following as benchmarks
 - Naïve estimate
 - Eurocontrol PRU (Capelleras, 2015)
 - FAA APO (2012)



Case study

- ATL airport
- 62 days of data (Dec 2019 and Jan 2020)
- ~136k movements in total (arr + dep)
- ~67k departures before removing outliers, ~62k after

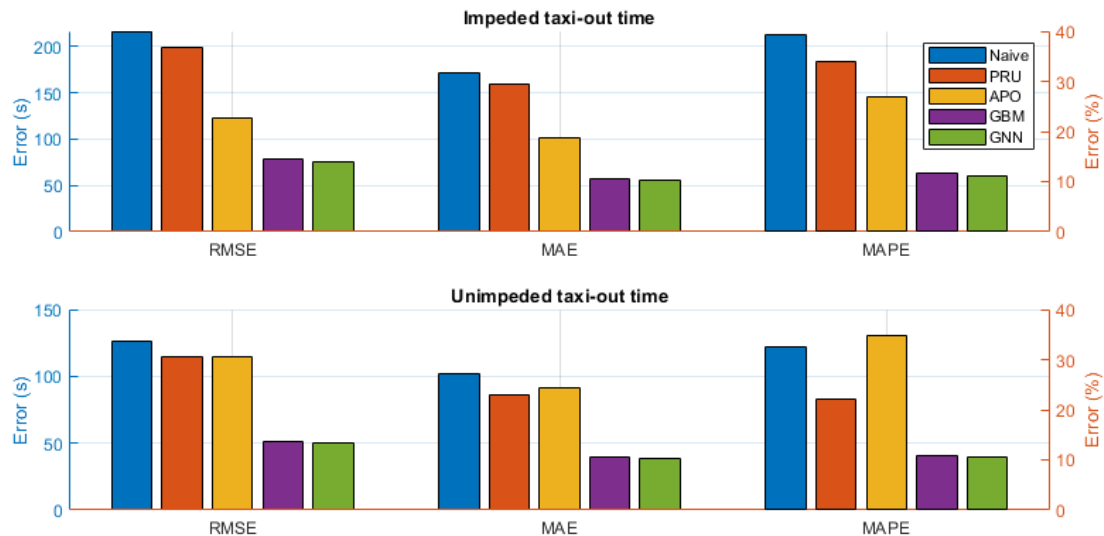


Stat	Value
Mean	10.2 mins
Median	9.3 mins
St. Dev.	5.2 mins
90 th perc	16.1 mins

n = 67,445

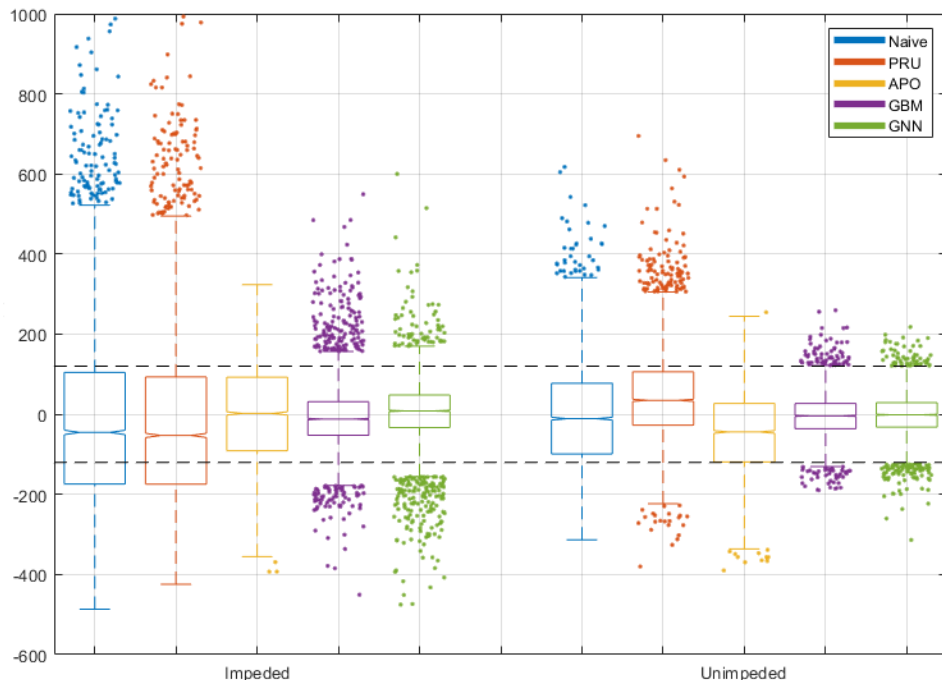
Results

- Naïve worst performer (MAE 3.6 min)
- APO (MAE 1.6 min), PRU (MAE 2.6 min), ML methods (MAE < 1 min)
- GNN and GBM models are on-par with each other



	Impeded			Unimpeded		
	RMSE	MAE	MAPE	RMSE	MAE	MAPE
Naïve	216.4s	171.9s	39.3%	126.2s	102.0s	32.6%
PRU	199.2s	159.8s	33.9%	115.1s	86.5s	22.1%
APO	123.1s	101.3s	26.8%	114.3s	91.4s	34.9%
GBM	78.4 s	57.3s	11.6%	51.1s	39.5s	10.9%
GNN	76.0s	55.2s	11.0%	50.1s	38.4s	10.4%

Results



Error range	GBM (s)	GNN (s)
[-120, 120]	[4.9, 94.9] (90.1%)	[5.0, 96.0] (91.0%)
[-90, 90]	[10.4, 91.2] (80.8%)	[8.9, 90.5] (81.6%)
[-60, 60]	[21.3, 84.6] (63.4%)	[15.0, 80.8] (65.7%)
[-30, 30]	[38.6, 74.3] (35.7%)	[26.6, 64.1] (37.5%)

Conclusions

- ML methods generally **outperformed** standard methods
- GNN performance was **slightly better** than the GBM one
- Model input data requirements were kept to what was assumed to be **operationally available**, relying primarily on the OBT and taxi route data
- A **graph-based framework** allows for the incorporation of spatio-temporal features such as traffic flow
- **Graph pruning** was an important contribution that helped reduce the amount of irrelevant information
- 90% of test dataset had a maximum error of **± 2 min** for ML models

Future work

- How **generalisable** is the model to different airports?
- What is the extent that the GNN performance can be improved by **additional data**?
- What **changes to flow features** can improve the GNN model performance?
- What **modifications to GNN architecture** can improve the model performance?
- How can the model be integrated into an **optimisation framework**?
- How useful as an **ATCO decision support tool**?

THANK YOU!

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