Predicting Airport Runway Configuration for Decision-Support Using Supervised Learning

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- Automated approaches based on Artificial Intelligence (AI) and Machine Learning (ML) can be used to improve the quality of the decision-making process by assisting the controllers.

Literature in runway configuration management

- **Prescriptive approaches**: main goal is to recommend the most optimal runway configuration.
  - Examples: search, optimization, dynamic programming, queuing theory, reinforcement learning.
  - Pros: it is interpretable and guaranteed to provide near-optimal solution.
  - Cons: performance heavily depends on the accuracy of model/simulation; any modeling error or over-simplification can result in a poor performance.

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- **Predictive approaches**: main goal is to learn human decision-making logic from historical data and reproduce it with least amount of error.
  - Examples: random forest, gradient boosted trees, deep neural networks.
  - Pros: easy to implement and can use vast amount of historical data. No need to build an airport-specific model.
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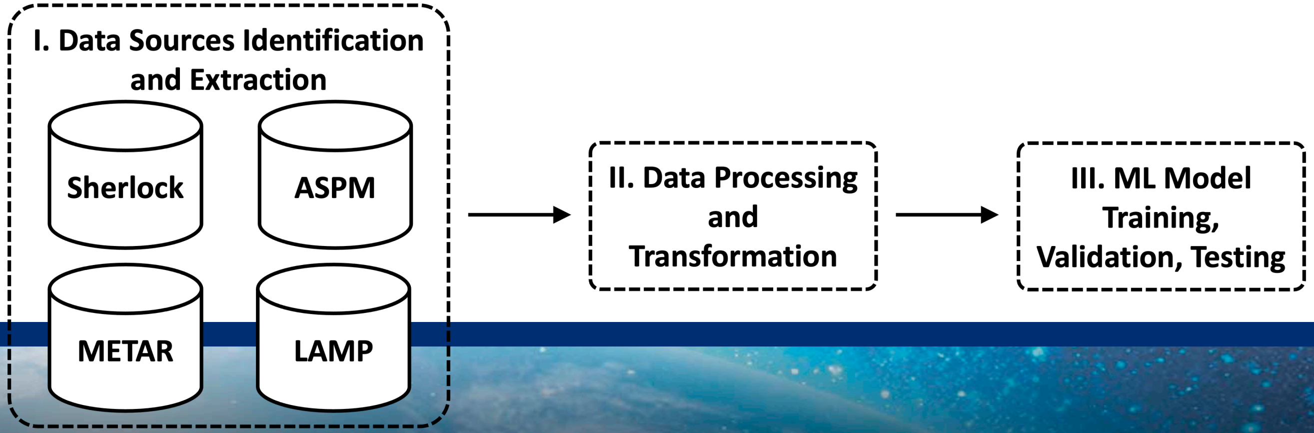
Both prescriptive and predictive approaches generally involve building a model using historical operations data. This model is either based purely on the data or requires detailed airport-specific adaptation.

Our Methodology

The main contributions of this work are:

- A comprehensive processing, fusion and analysis of historical data related to runway configuration management and **preparing the most complete set of ML-ready data for RCM**:
  - Current weather data from METeorological Aerodrome Reports (METAR).
  - Forecast of weather from Localized Aviation Model Output Statistics Program (LAMP).
  - Traffic operational data from the FAA's Aviation System Performance Metrics (ASPM).
  - Safety/efficiency-related data from NASA's Sherlock Data Warehouse.



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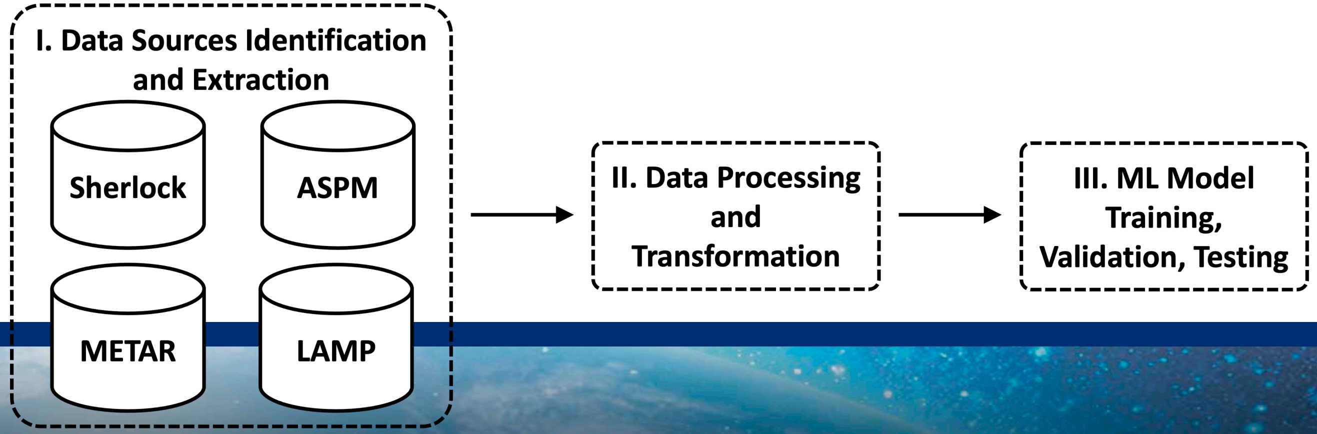
- A comprehensive **implementation of predictive models** for runway configuration management. The main goal is to learn, as closely as possible, decision-making logic in the historical data, to predict runway configurations for the future.



Problem Setup

The building blocks of the RCM predictive model

Runway configuration at CLT

CLT has two major configurations:
North flow and South flow.

Major runway configurations for CLT

Configuration [Arr/Dep]	Arrival Runways	Departure Runways	Usage Frequency [%]
N/N	36C/L/R	36C/R	60.8
S/S	18C/L/R	18C/L	39.2

Runway configuration at CLT

CLT has two major configurations: North flow and South flow.

There is a strong correlation between the wind conditions and the choice of runway configuration.

Major runway configurations for CLT

Configuration [Arr/Dep]	Arrival Runways	Departure Runways	Usage Frequency [%]
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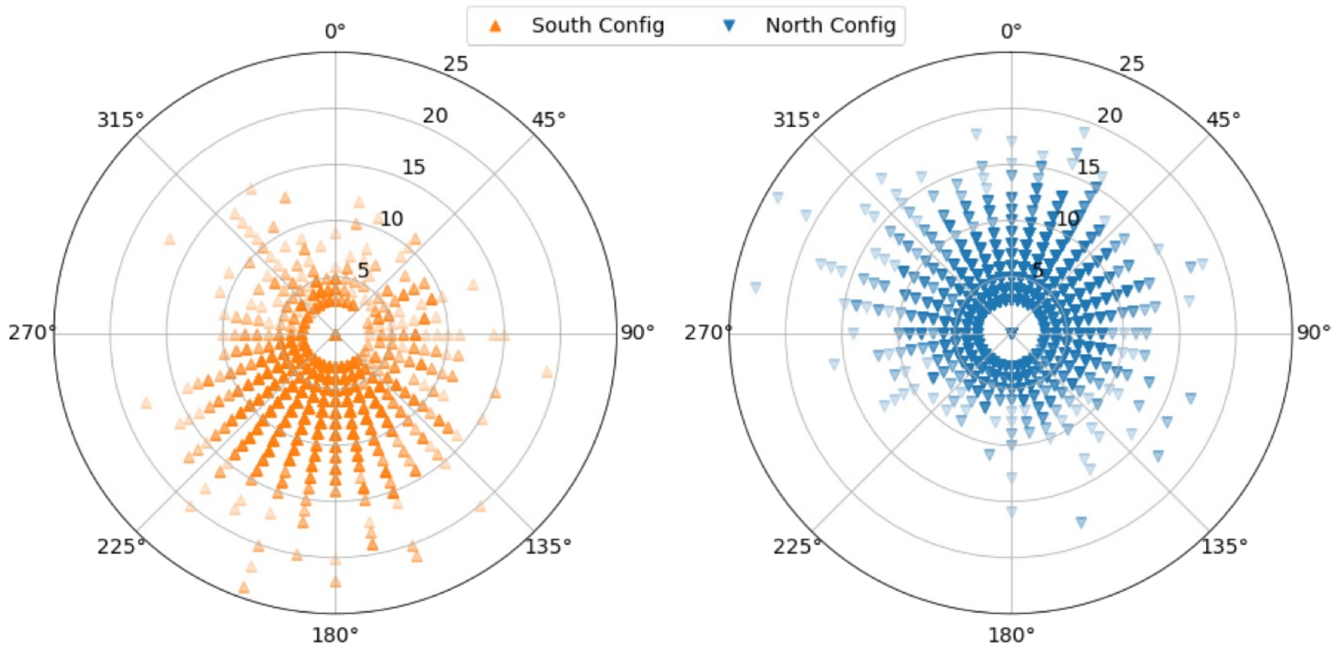
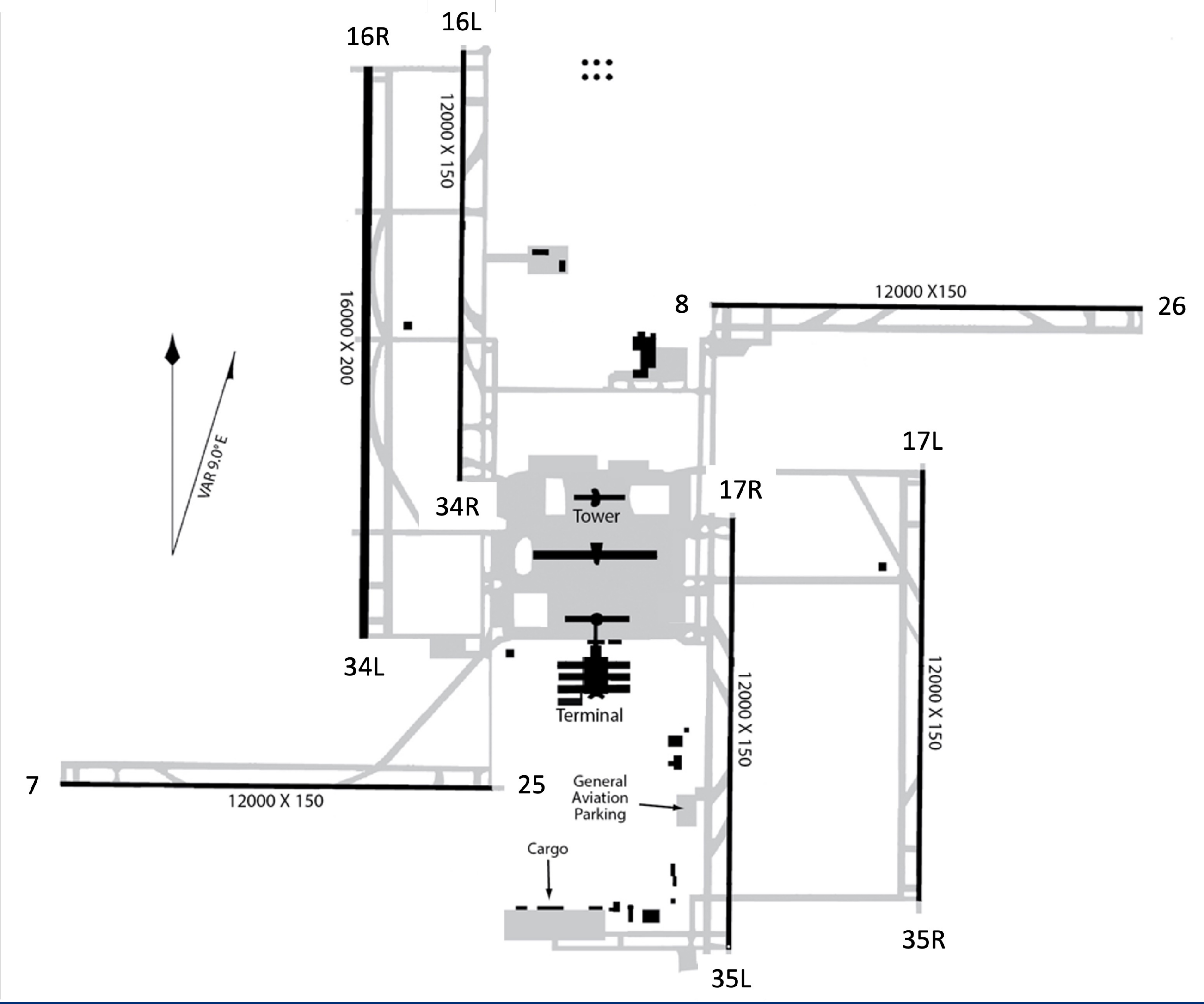


Runway diagram & configuration at DEN



Major runway configurations for DEN

Configuration [Arr/Dep]	Arrival Runways	Departure Runways	Usage Frequency [%]
SE/SE	16R/L, 17R/L, 7, 8	16R/L, 17R/L, 7, 8	18.8
S/S	16R/L, 17R/L	16R/L, 17R/L	15
N/NEW	34R/L, 35R/L	34R/L, 35R/L, 8, 25	14.5
S/SEW	16R/L, 17R/L	16R/L, 17R/L, 8, 25	12.6
N/N	34R/L, 35R/L	34R/L, 35R/L	12.3
NE/NE	34R/L, 35R/L, 7, 8	34R/L, 35R/L, 7, 8	11.7
NW/NW	34R/L, 35R/L, 25, 26	34R/L, 35R/L, 25, 26	8.6
SW/SW	16R/L, 17R/L, 25, 26	16R/L, 17R/L, 25, 26	3.4
E/E	7, 8	7, 8	1.6
NS/EW	34R/L, 35R/L, 16R/L, 17R/L	8, 25	1.2
W/W	25, 26	25, 26	0.3

USRA

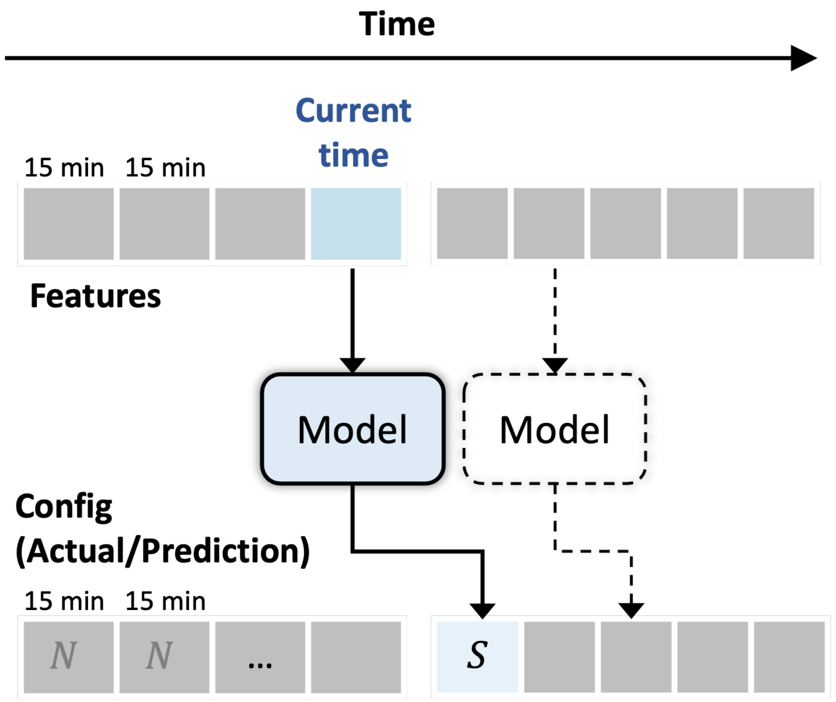
Data processing and fusion

Data Source	Feature	Type
METAR	Wind Direction	Categorical
	Wind Speed	Numerical
	Ceiling, Visibility, Temperature	Numerical
	Meteorological Condition	Categorical
ASPM (FAA)	Local Hour & Quarter Hour	Categorical
	Scheduled Arrivals/Departures	Numerical
	Capacity Arrivals/Departures	Numerical
	Runway configuration	Categorical
Sherlock (NASA)	Number of go-arounds	Numerical
	Multiple go-arounds	Categorical
LAMP (NOAA)	Wind Direction Forecast	Categorical
	Wind Speed Forecast	Numerical
	Forecast of Ceiling, Visibility, Temperature	Numerical
	Precipitation Forecast	Categorical
	Convection Forecast	Categorical
	Lightning Forecast	Categorical
	Meteorological Condition Forecast	Categorical

Predictive model setup

Supervised imitation learning:

- We built a model based on random forests to learn, as closely as possible, **the decision-making logic** by the air traffic controllers based on historical data.
- Once trained, the model can make predictions about what the controllers are likely to do in certain situations.



Results & Discussion

The unbiased performance of the model in CLT and DEN

Performance metrics

We processed and fused two years (2018 and 2019) worth of data and divided them into **two sets of training (80%) and testing (20%)**.

After finding optimum values of the hyper-parameters, we estimate the **unbiased performance of the model** on the testing set, i.e., a set of data unseen by the model during training.

Baseline model mimics the most frequent controller decisions, which shows the considerable variations in the controllers' decision-making. It also emphasizes that our approach out-performs policies based on simple aggregate statistics.

Overall model performance (15-minutes ahead prediction)

Airport	Training Accuracy	Testing Accuracy	Testing F-1 Score	Baseline model
CLT	98.94	93.94	93.96	81.6
DEN	96.45	73.49	74.05	53.7

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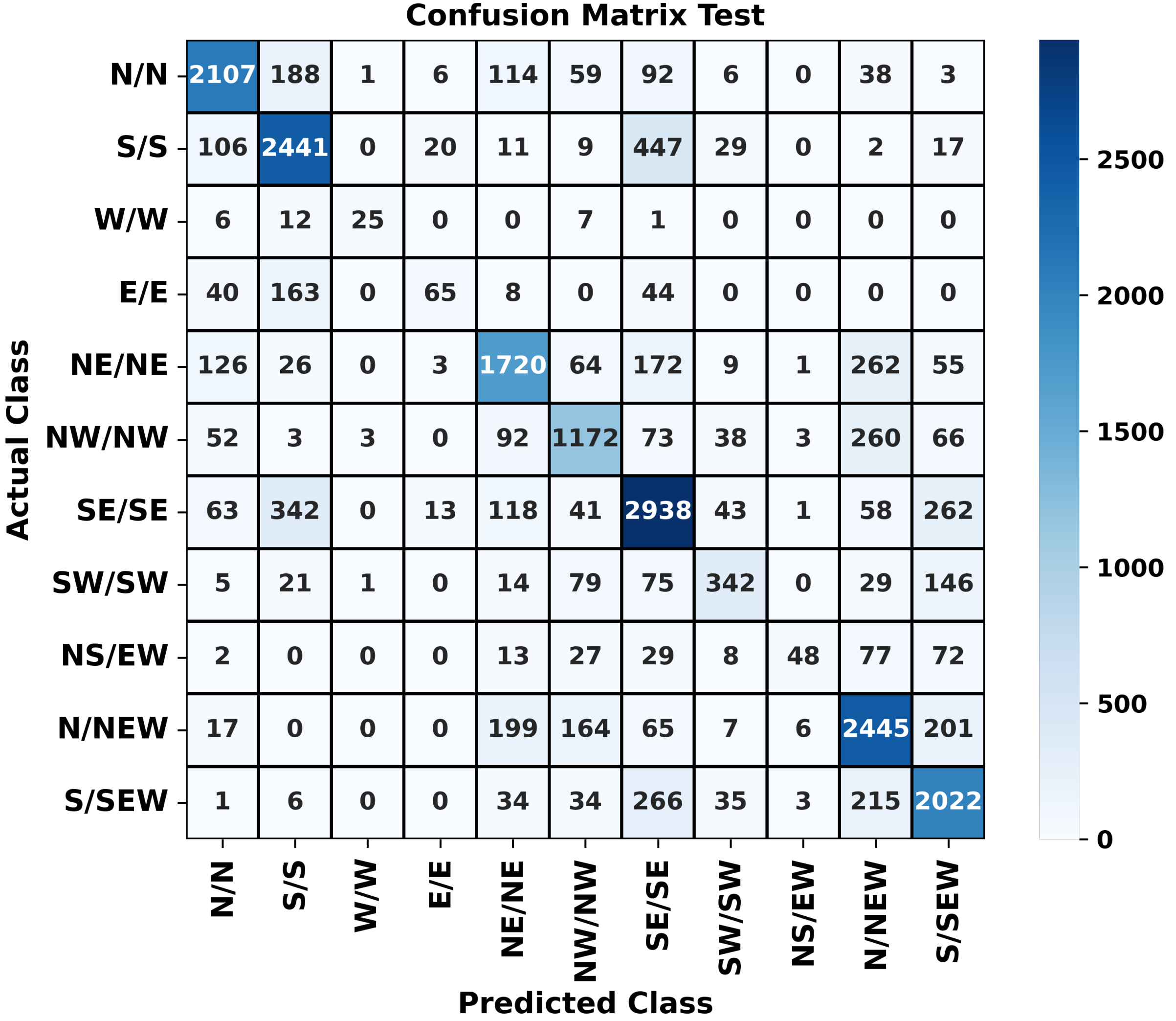
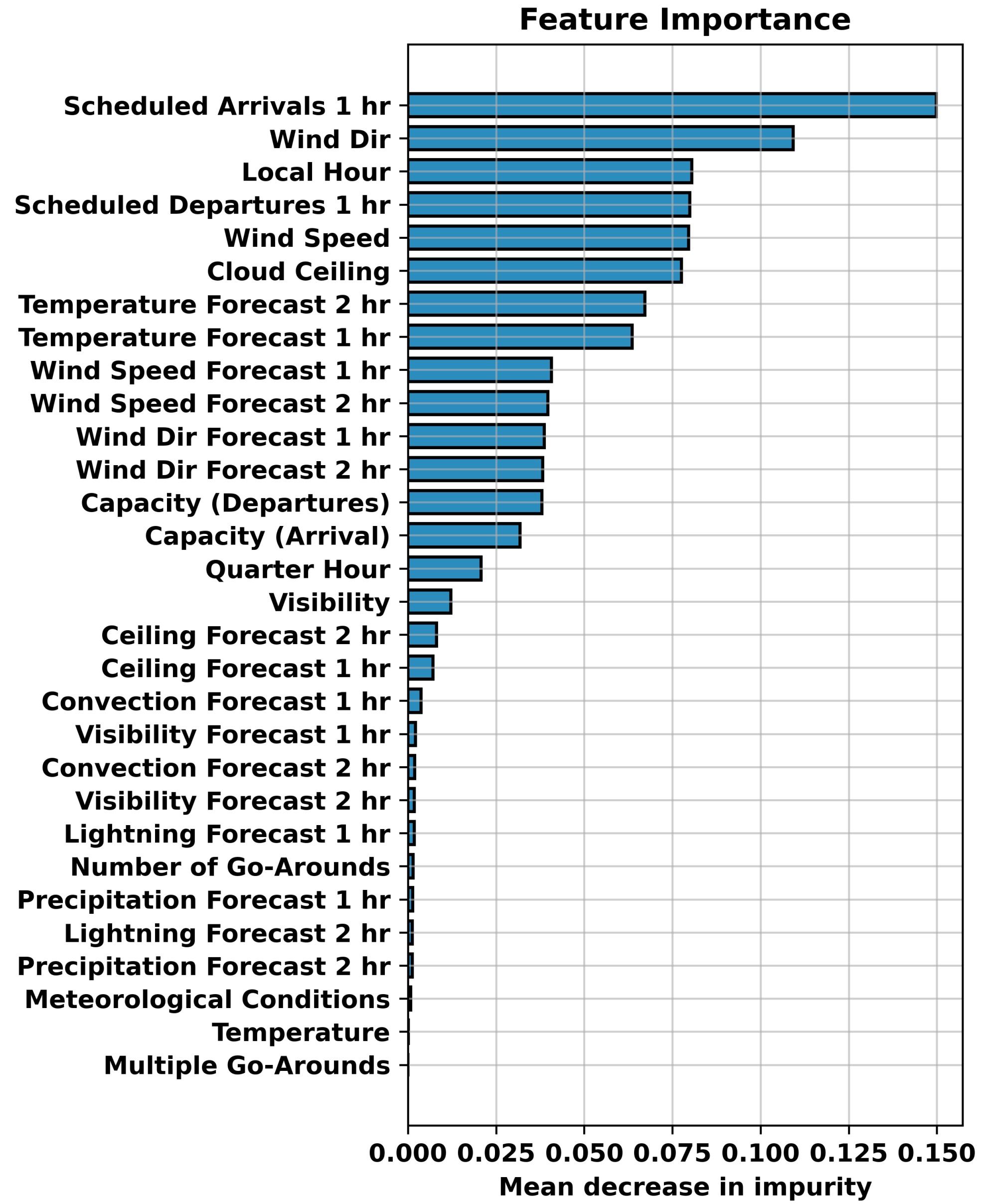


Important features in model's inference: DEN

Random forest model can generate feature importance using a method called **mean decrease in impurity**. In simple terms, it counts the times a feature is used to split a node, weighted by the number of samples it splits.

One of the drawbacks of this method is that the importance can be high even for features that are not predictive of the target variable, as long as the model has the capacity to use them to overfit.



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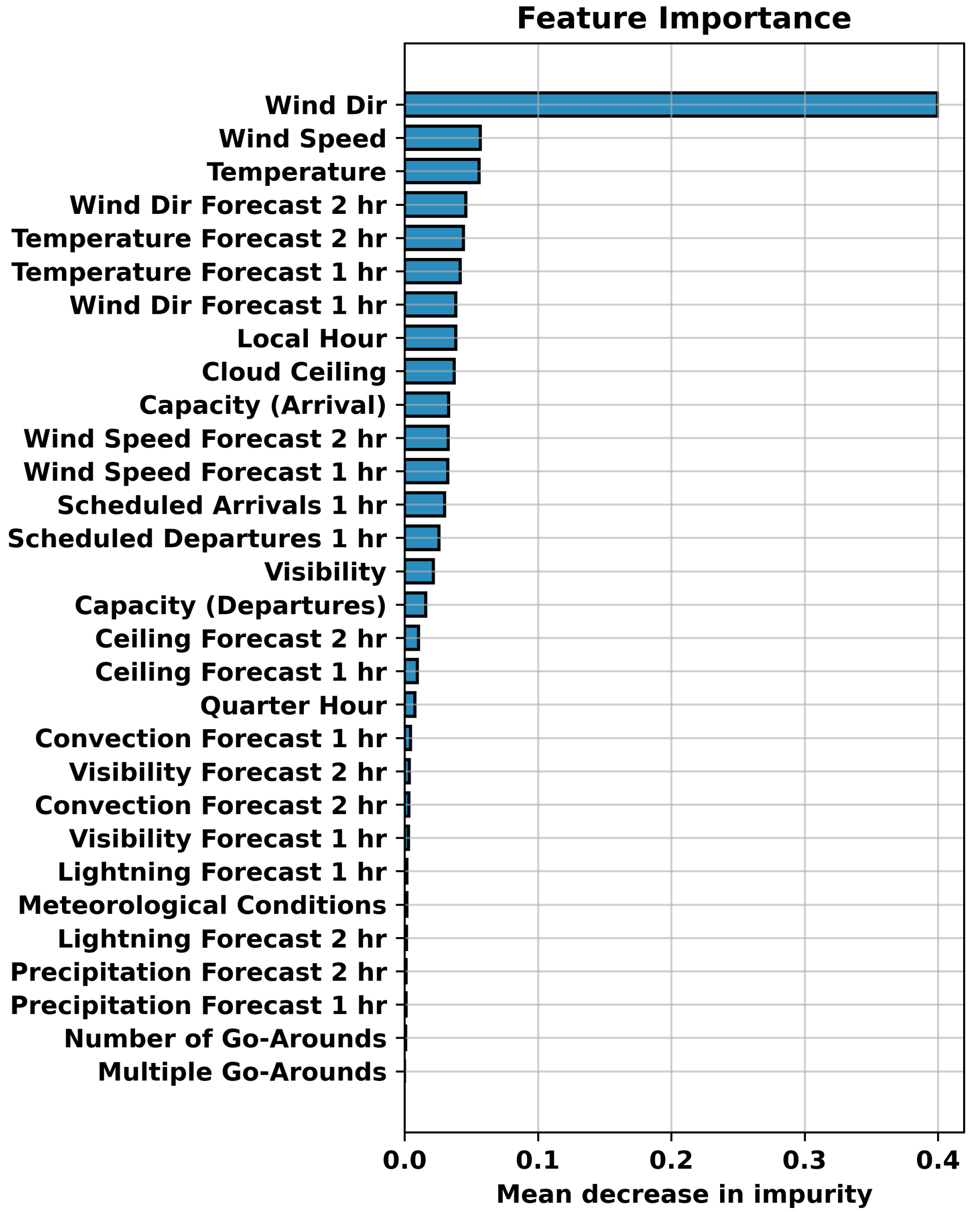

Concluding remarks and next steps

We deployed a supervised imitation learning algorithm for runway configuration management and show that it performs well on both examples of a simple airport (CLT) and a complex airport (DEN).

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Next Steps involve:

- Inclusion of weather forecast data from **Terminal Aerodrome Forecast** (TAF) source.
- **Extend the developed ML pipeline** to major airports across the NAS.
- Improve the **explainability of model's inference** using techniques such as SHapely Additive exPlanations (SHAP).
- Explore applications of more advanced ML models such as **recurrent neural networks** that can explicitly account for the temporal nature of the data.

Thank you.

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Questions?