A Multi-Layer Artificial Neural Network Approach for Runway Configuration Prediction

Never Stand Still

Authors:

Md Shohel Ahmed[1], Dr. Sameer Alam[2] and Dr. Michael Barlow[1]

[1]School of Engineering and Information Technology, UNSW, Australia.

[2]School of Mechanical & Aerospace Engineering, NTU, Singapore.

Outline

- Problem Definition
- Research Question
- Problem Formulation
- Proposed Methodology
- A Case Study at Amsterdam, Schiphol
- Experiment and Simulation Result
- Conclusion and Discussion

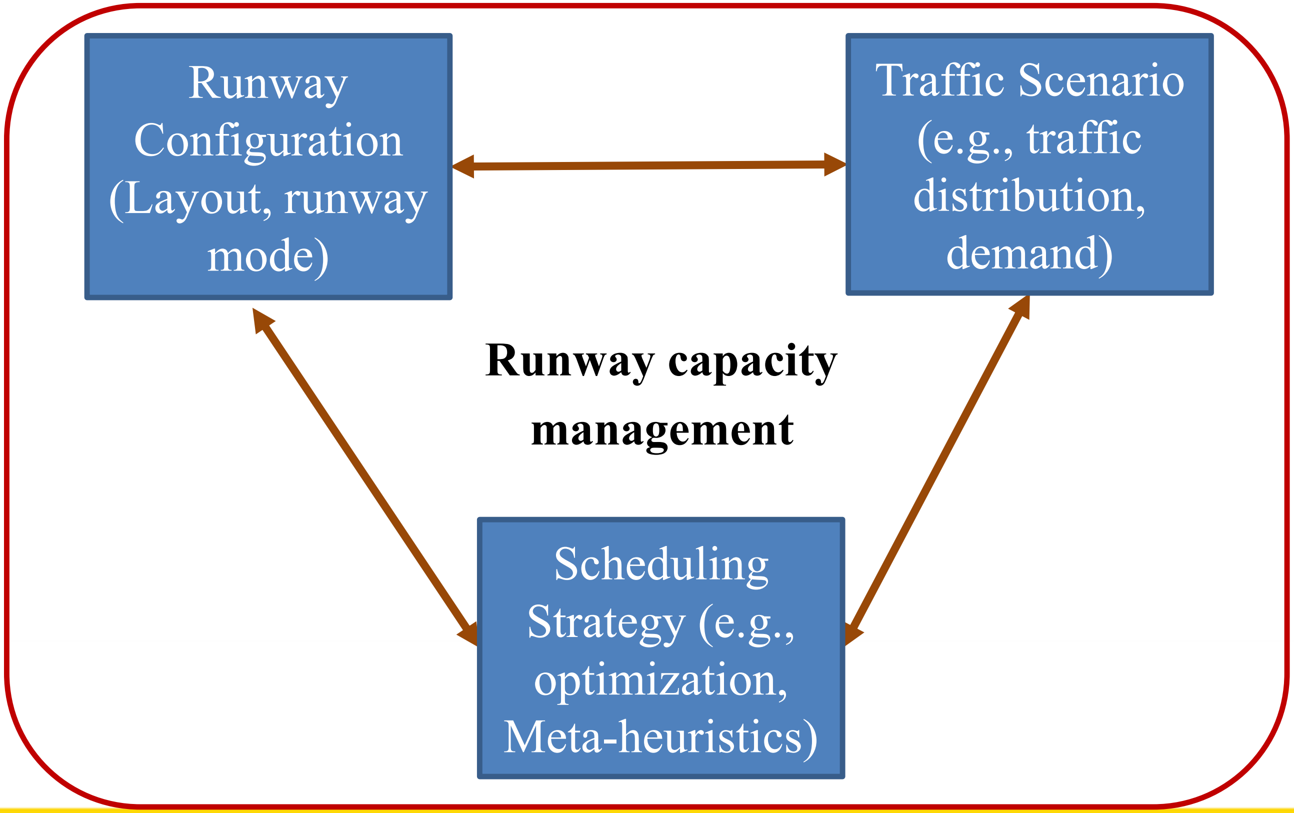
Problem Definition

- Continued growth in air traffic
  - lead to congestion
  - prolonged delays

- Possible solution approaches
  - Increase the capacity in air
  - Increase capacity in ground (runway)

Problem Definition

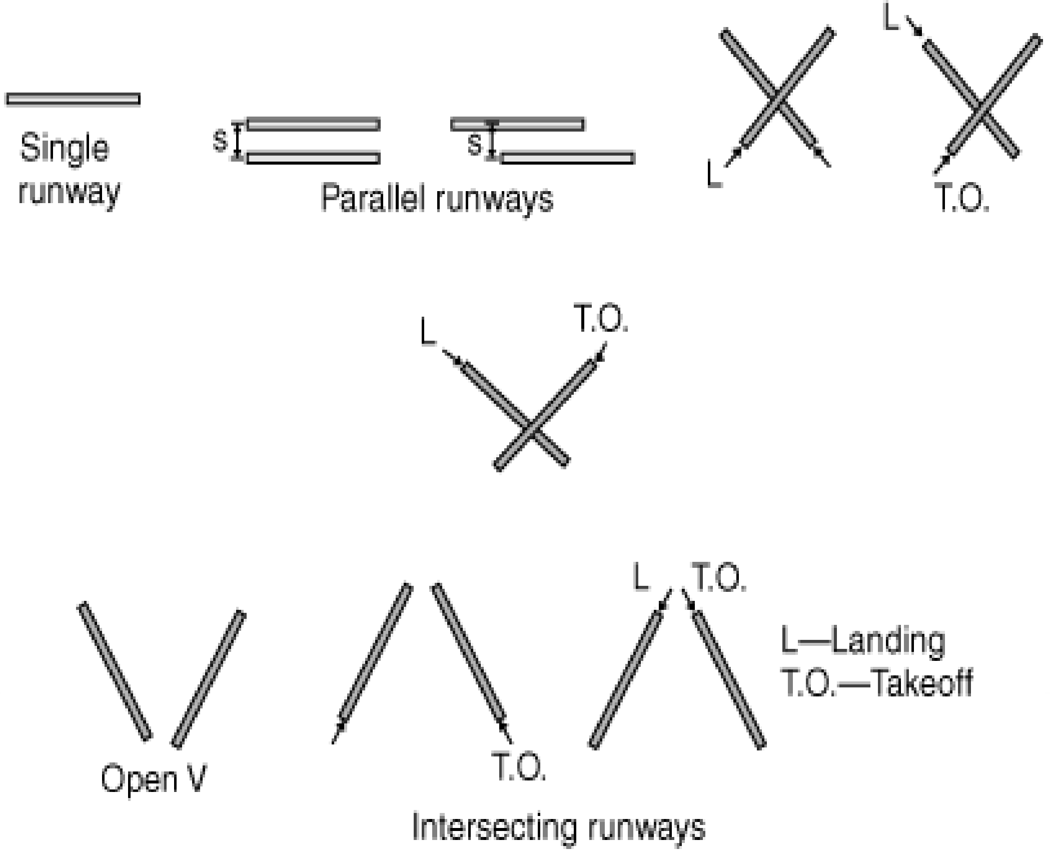
- Way to enhance the runway capacity
  - Infrastructure development (e.g., new runways)
  - Efficient utilization of resources



Problem Definition

- Runway Configuration
  - Significant impact on the hourly capacity

- Parallel: High throughput
- Intersecting: least throughput



UNSW CANBERRA

Problem Definition

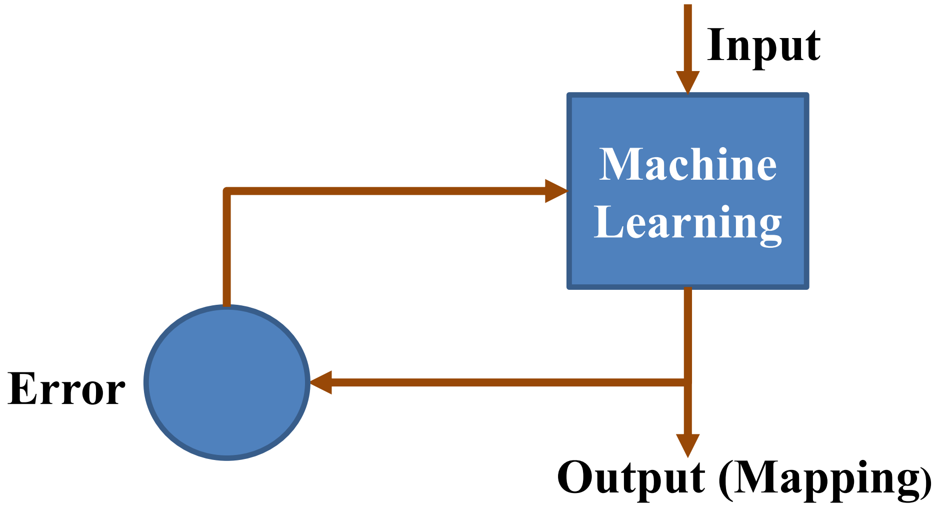
- Runway configuration selection involves several factors
  - Wind direction
  - Wind speed
  - Visibility
  - Cloud ceiling
  - QNH
  - Operation time
  - Air traffic distribution
- Predicting runway configuration might be a possible solution
  - Capacity enhancement
  - Efficient traffic planning

Research Question

- Can a machine learning algorithm predict runway configuration under various operating and weather conditions?

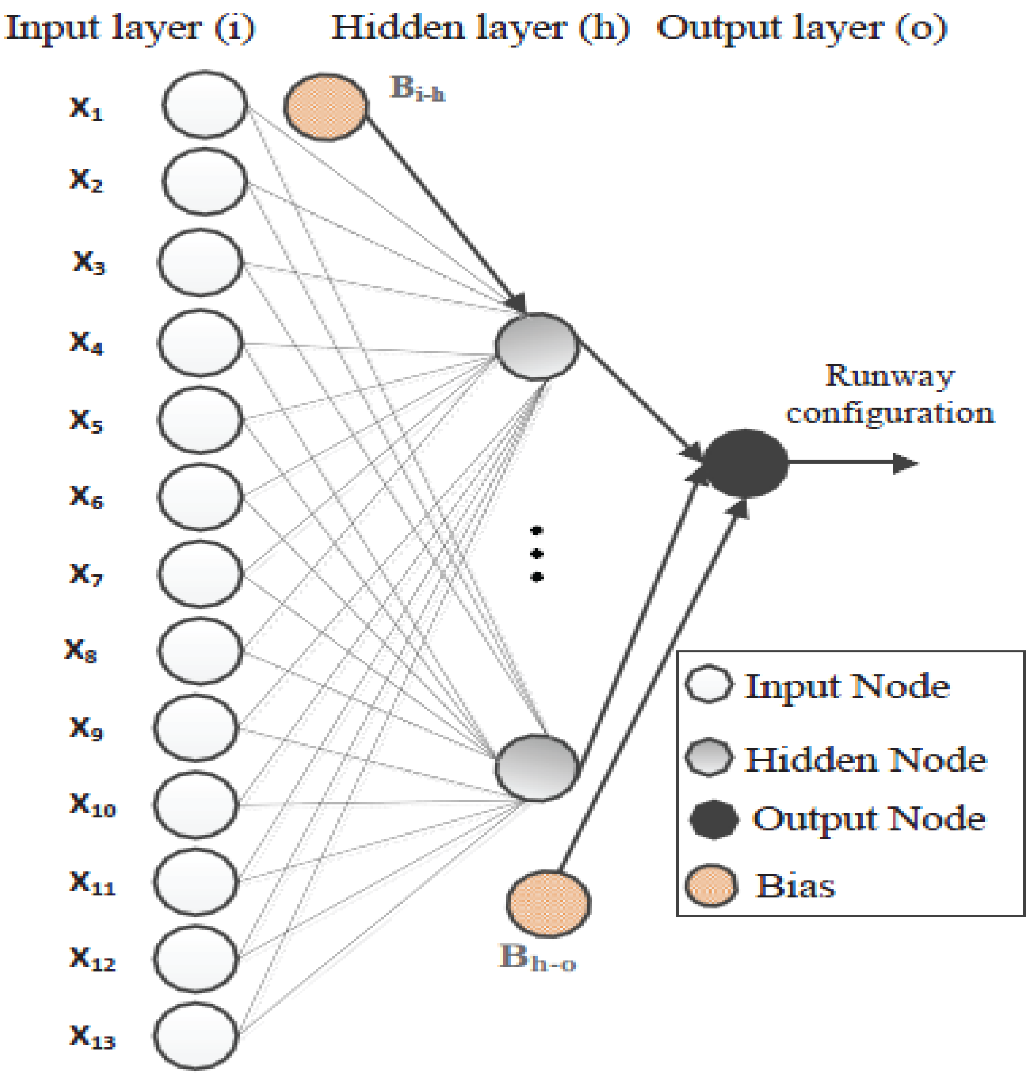
- Is it possible to enhance runway capacity by early configuration prediction?

Problem Formulation



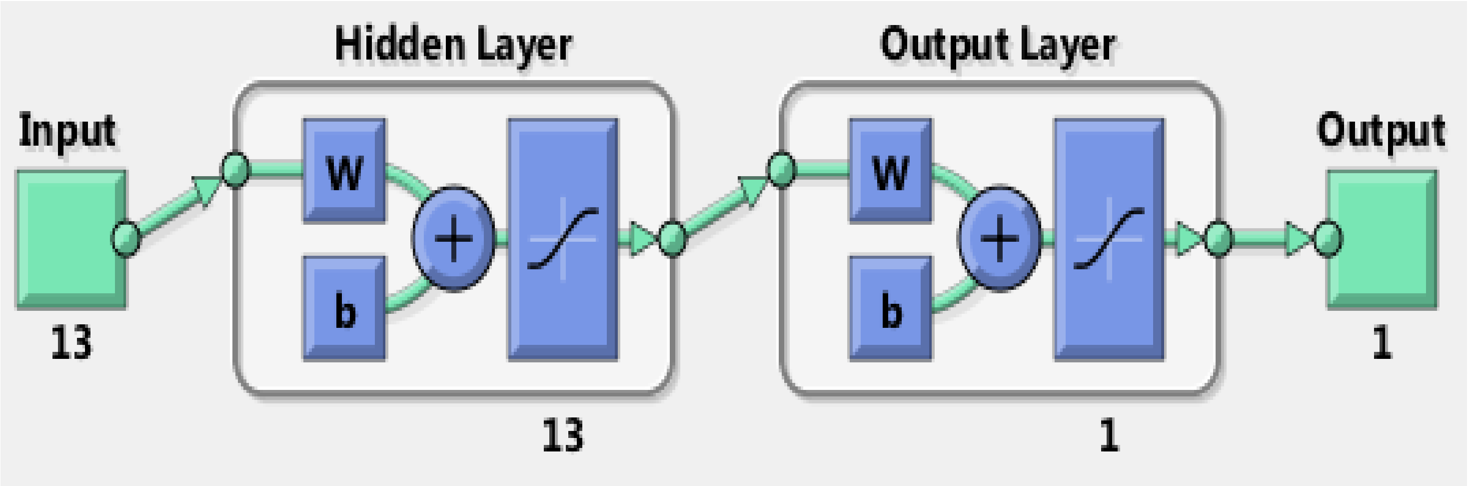
- Machine learning algorithm can
  - learn from data
  - make predictions from the data

Problem Formulation



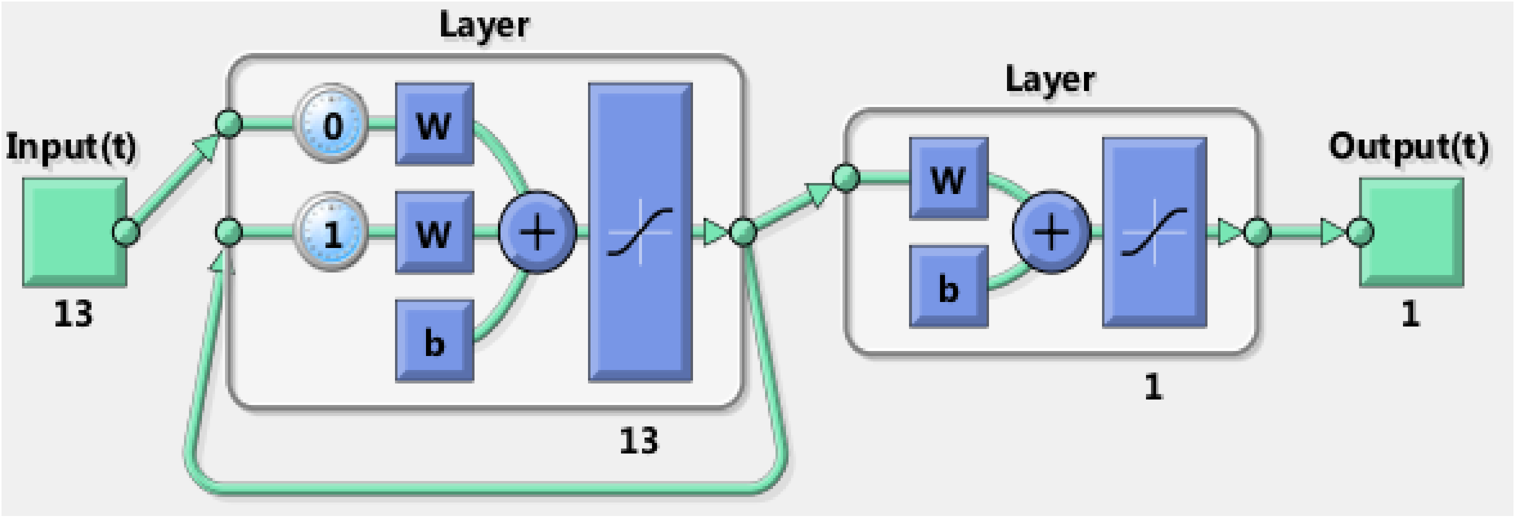
Problem Formulation

- Multi-layer Artificial neural network architecture
  - Feed-forward neural network
    - It learns and improve its accuracy when learning progresses
    - Map the inputs to the output

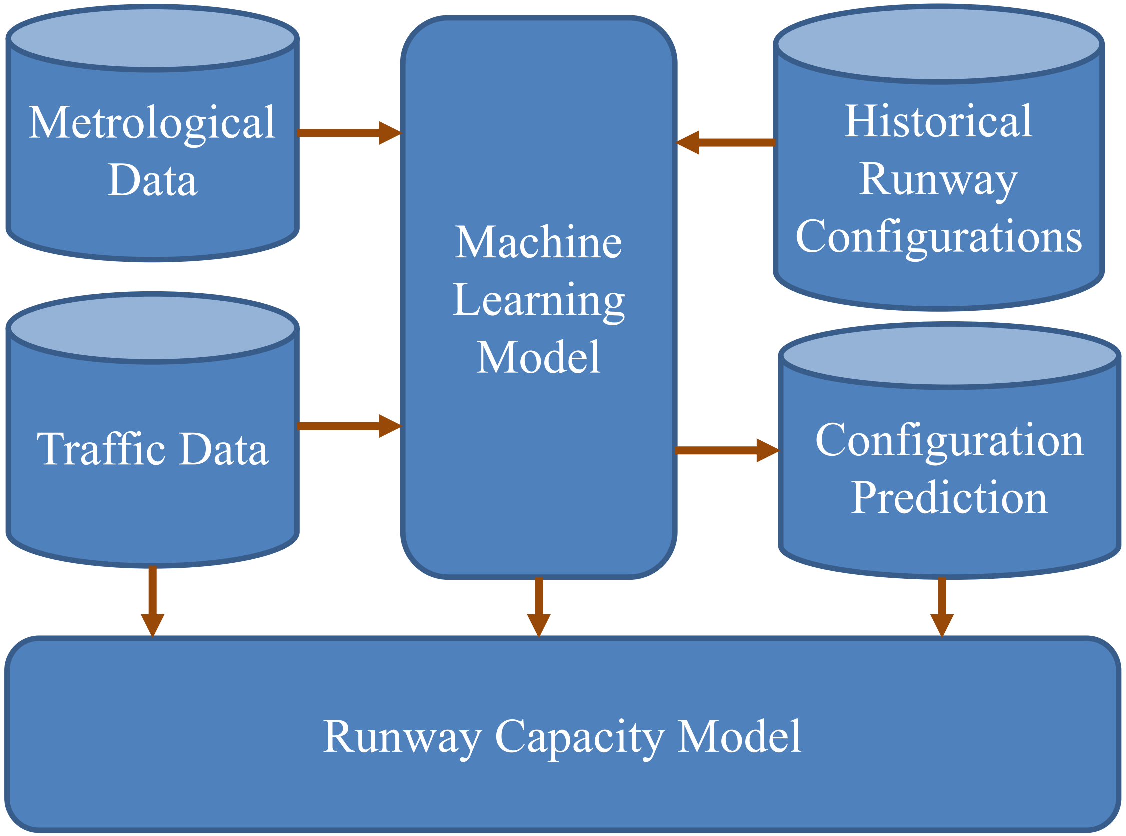


Problem Formulation

– Recurrent back propagation
  - Layer recurrent takes delayed output of the hidden layer
  - The delayed layer output is modified by a weight.



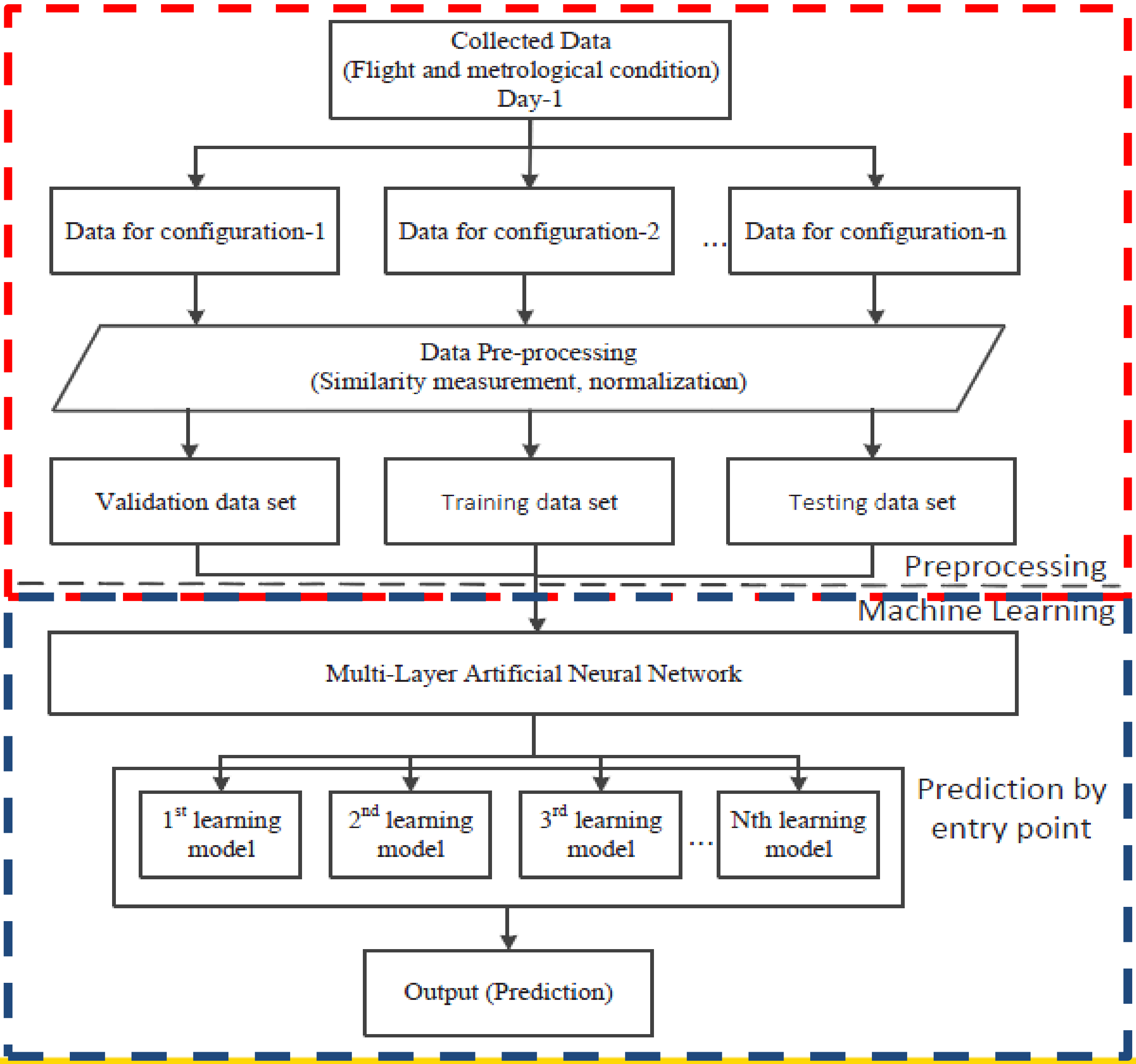
Proposed Methodology



Proposed Methodology

- **Data pre-processing**

- **Machine Learning**

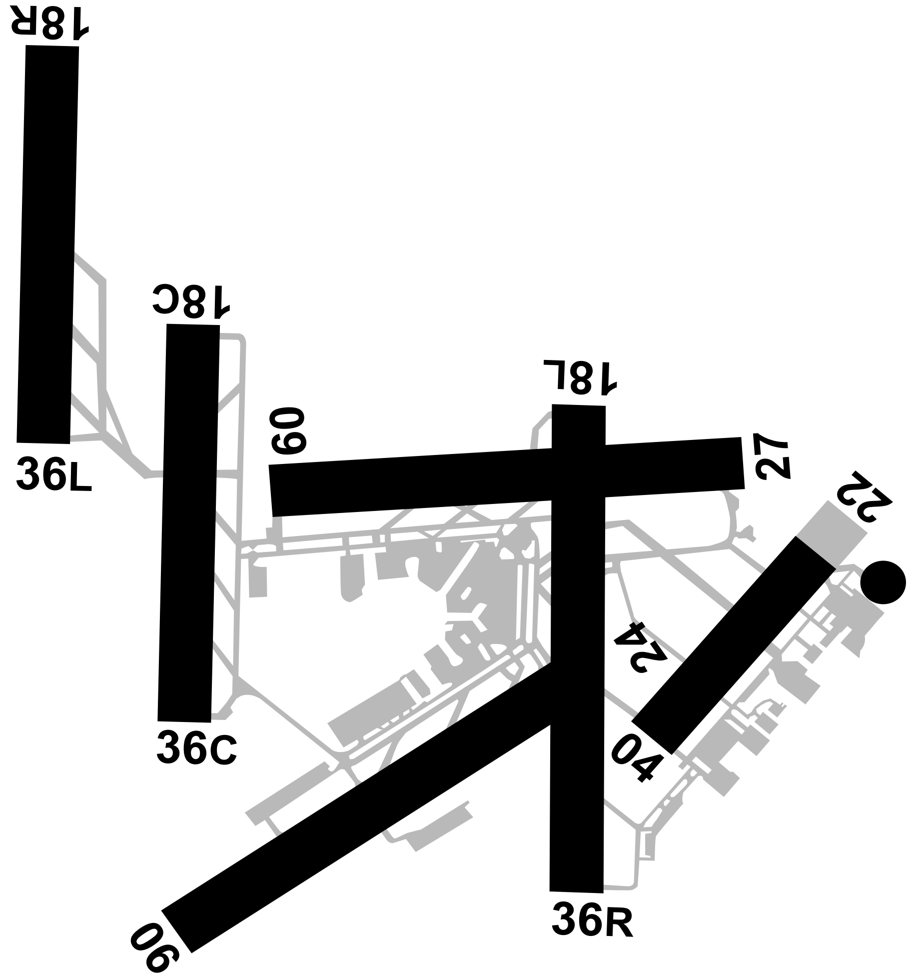


Proposed Methodology

- The model has two major steps
  - Data pre-processing
    - Collection of historical data
      - metrological data, traffic data, runway configurations
    - Data redundancy reduction
    - Data standardization
  - Machine learning
    - Train, test and validate the model

A case study: Amsterdam Schiphol airport

- **Six runways**
- **Multiple runway layout**
- **Frequently changing configurations**
- **One of the busy airport in Europe**

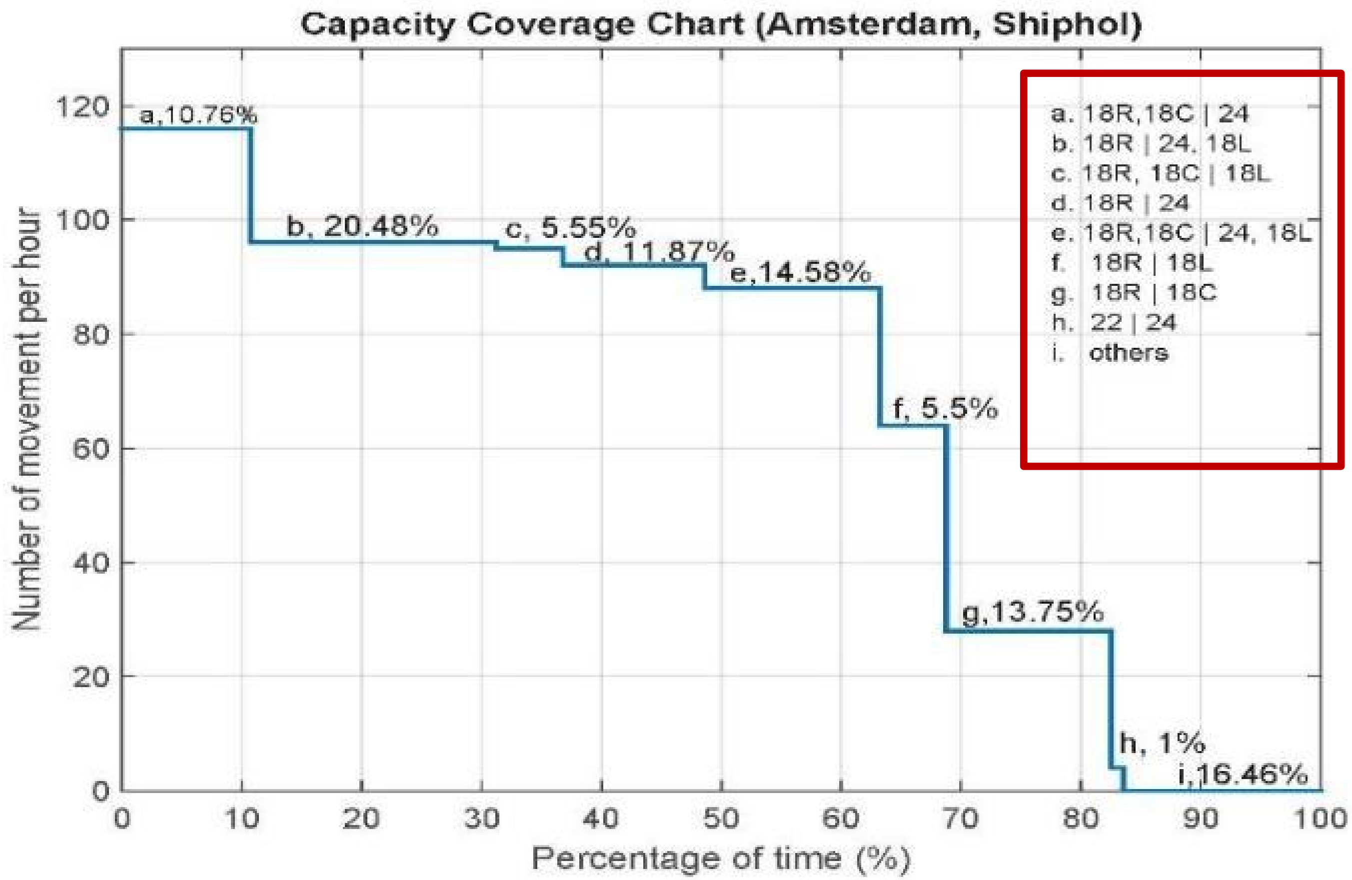


UNSW CANBERRA

Data Pre-processing

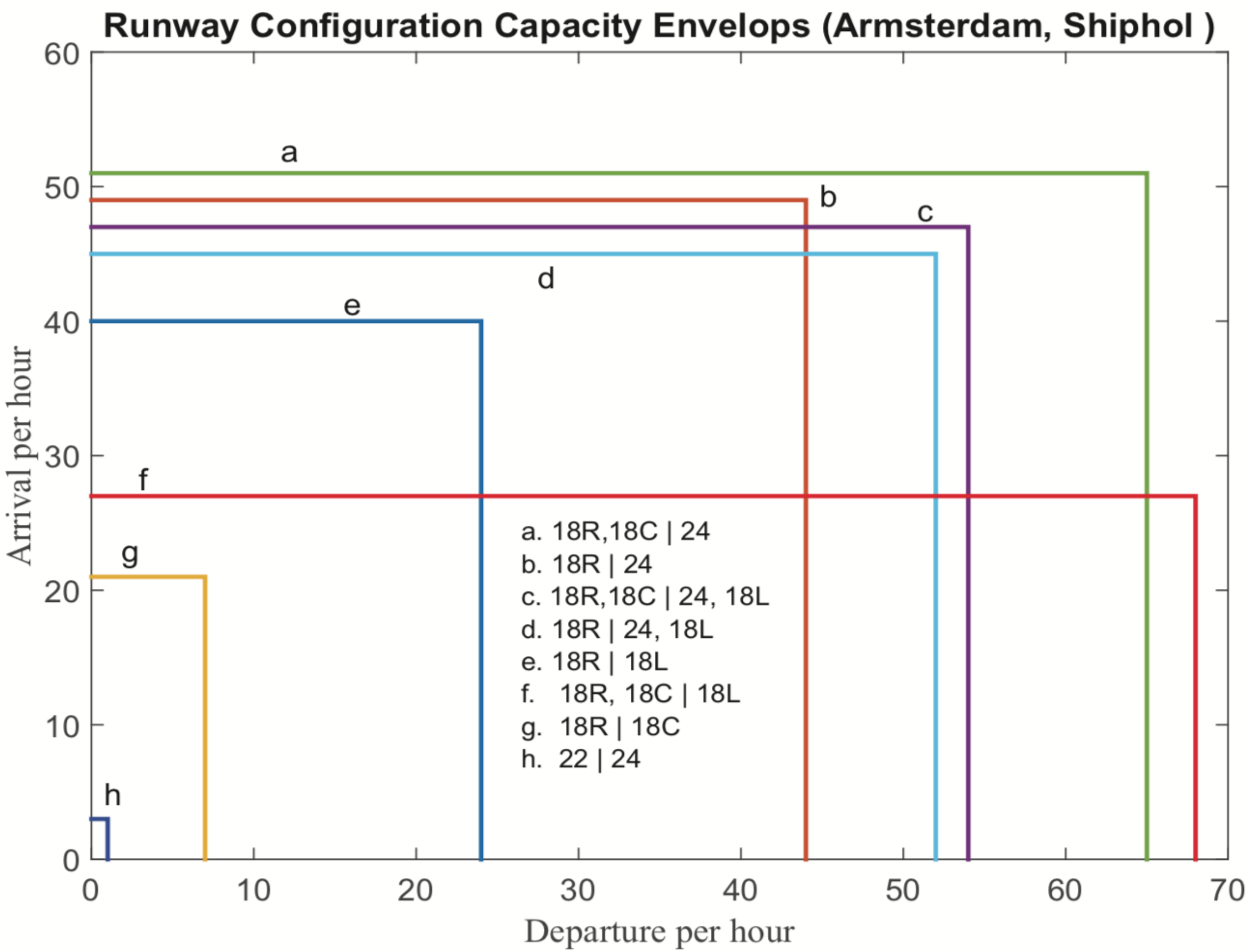
- Extracted data from Amsterdam Schiphol airport
  - Historical runway configuration
  - Traffic data (Aircraft arrival and departure distribution)
    - Heavy, medium and small aircraft
  - Metrological data
    - METAR
  - Issue time, wind direction, wind speed, visibility, cloud ceiling, air temperature, dew-point and QNH

Data Pre-processing



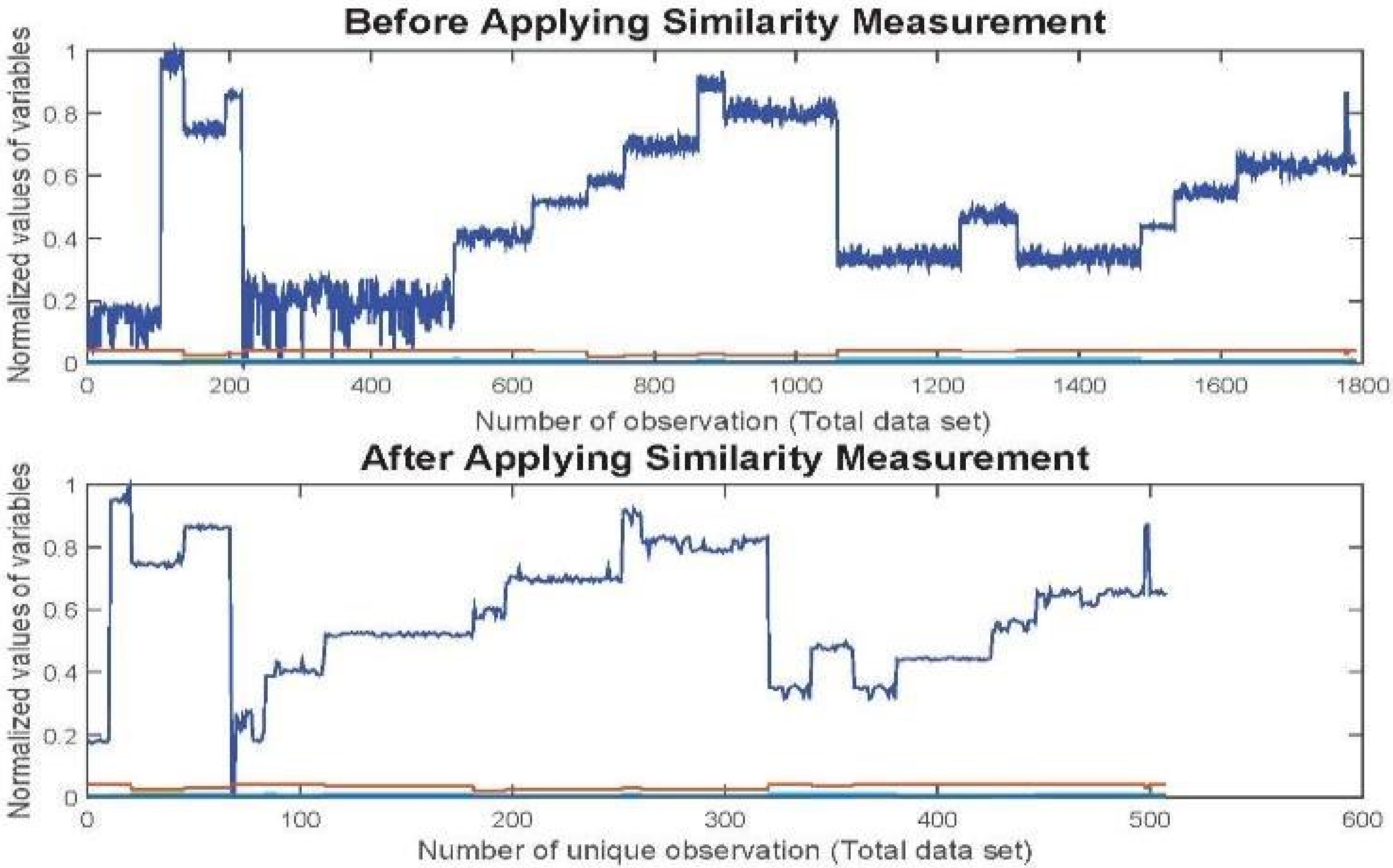
➢ **The Capacity Coverage Chart (CCC) shows how much runway capacity is available for what percentage of time**

Runway Capacity Envelope



UNSW CANBERRA

Data Pre-processing: Redundancy reduction



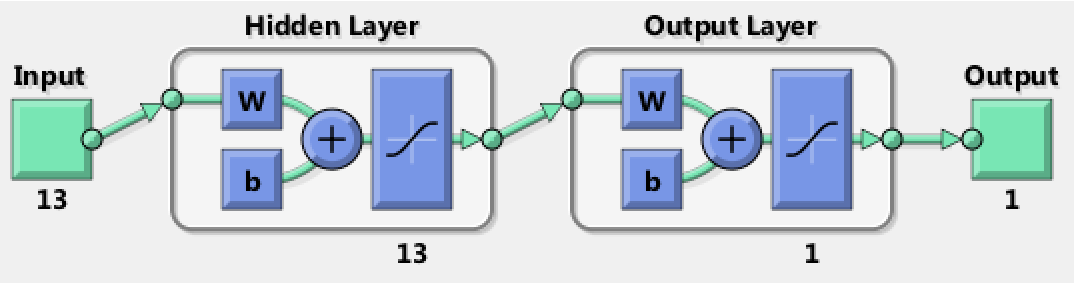
- **Data similarity measurement removes the redundant data from the total dataset**

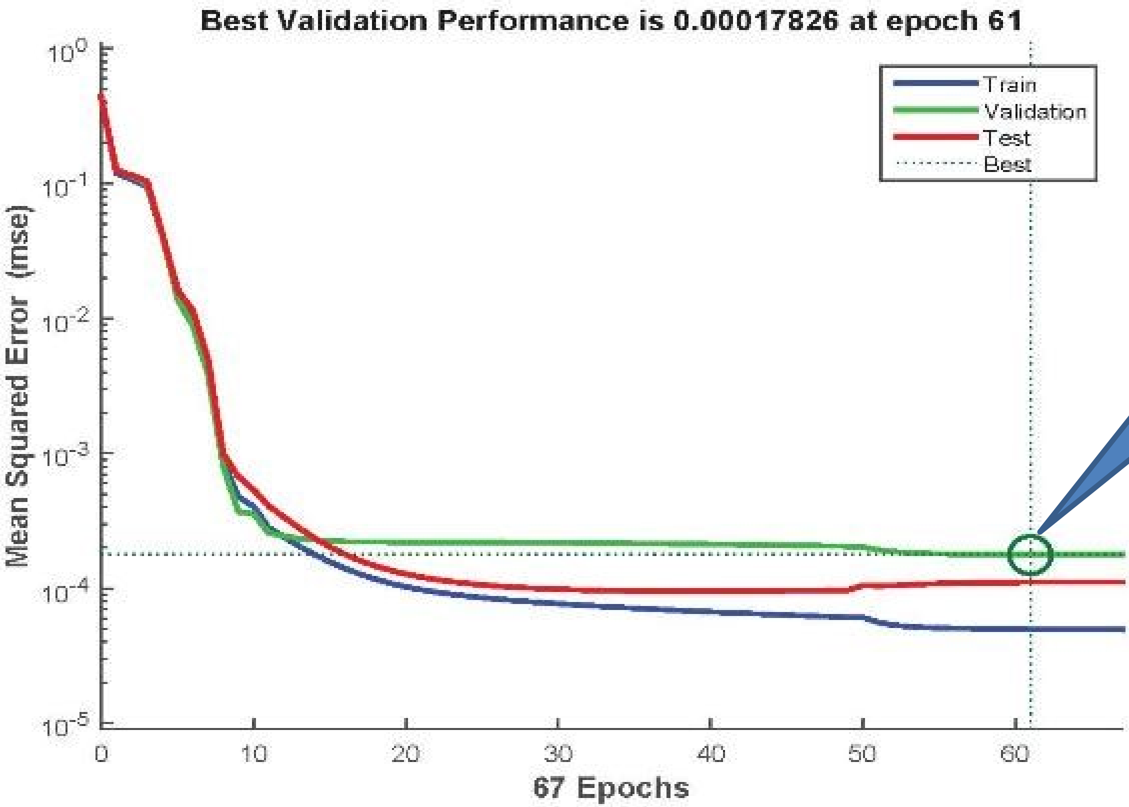
UNSW CANBERRA

Experiment Parameters

Description	Parameters
Data subset (Training, testing and validation)	70%, 15% and 15%
Learning rate	0.001
Error function	MSE (Mean Square Error)
Activation Function	Tan-Sigmoid

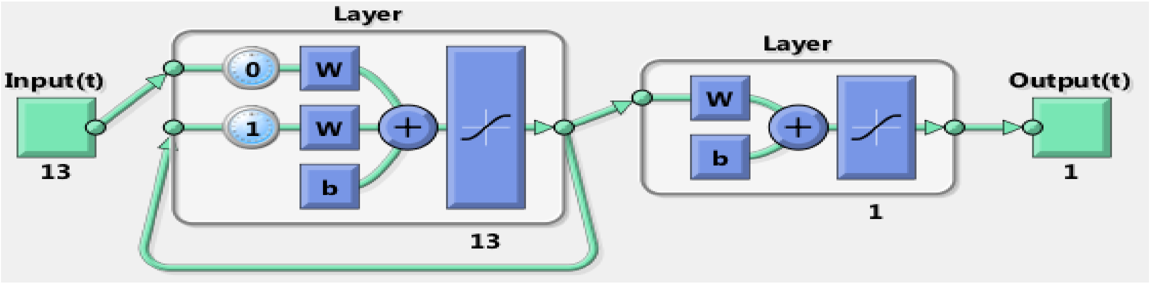
Feed-forward Neural Network

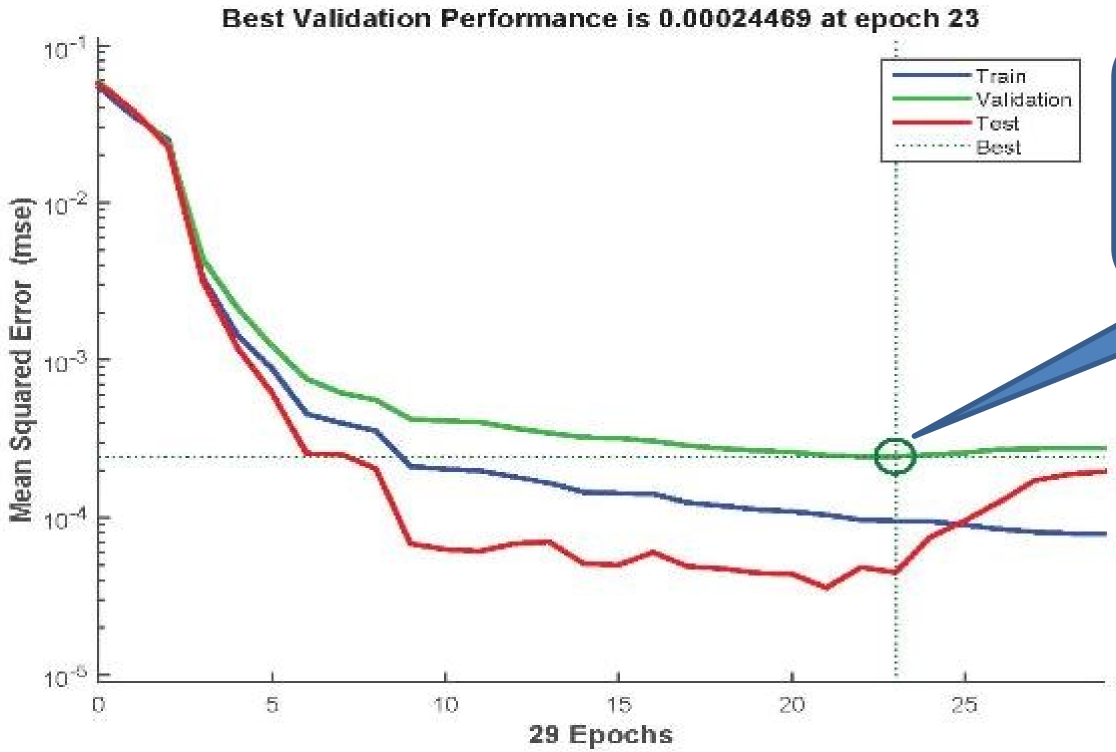




Best validation at 61 epoch

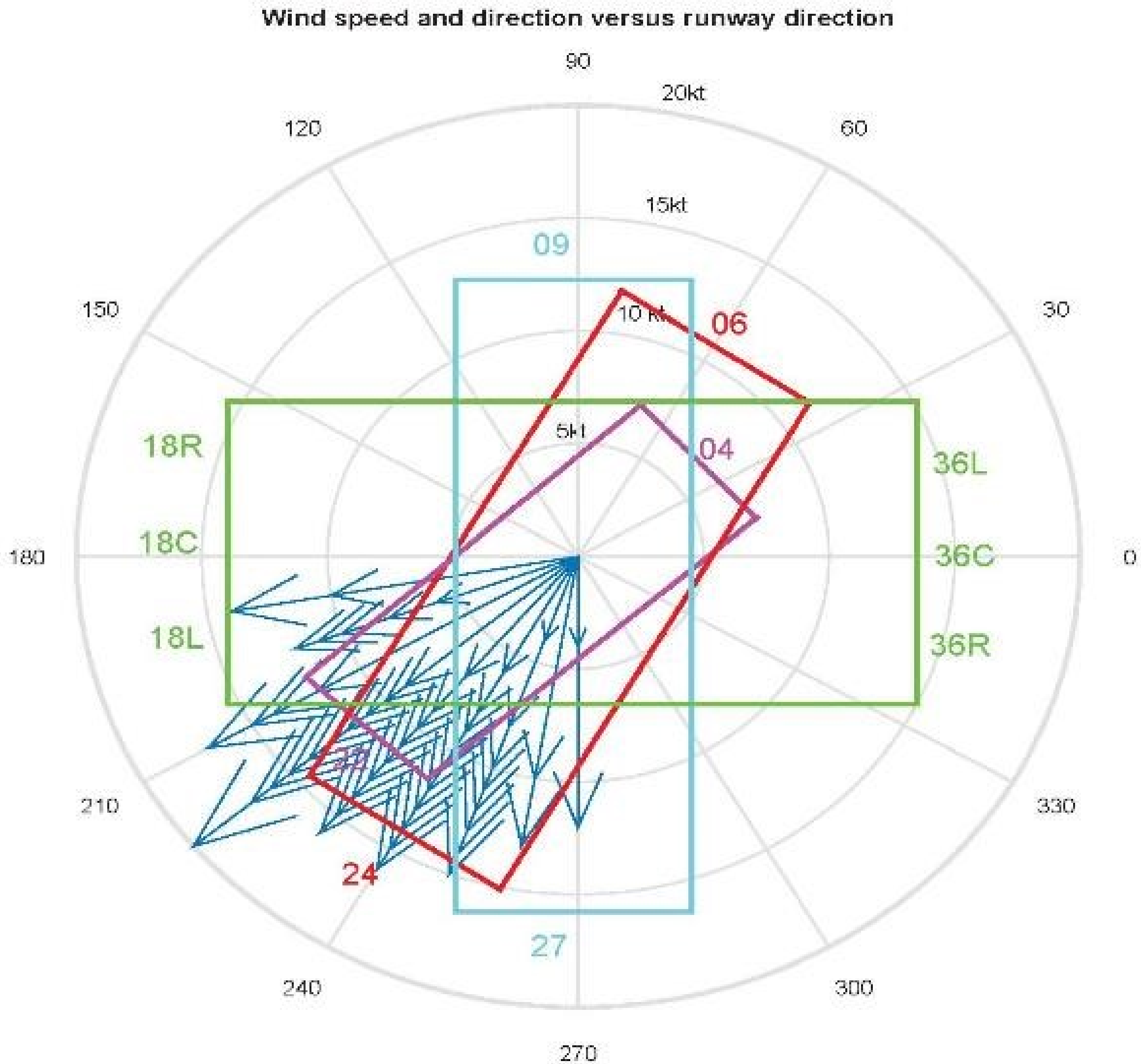
Recurrent Neural Network





Best validation at 23 epoch

Experiment and Result



- Based on wind direction and speed favourable runways:
- 18L / 18C / 18R,
- 06 / 24,
- 04 / 22
- and 27 / 09

UNSW CANBERRA

Experiment and Result

- The capacity of the forecasted runway configuration is projected:

S. N.	Used Configuration	Active time(%)	Movement/ hr	MLA prediction	Movement/hr (Predicted)
1	18R | 24	11.87%	92	18R, 18C | 24, 18L	136
2	18R; 18C | 24; 18L	14.58%	88	18R; 18C | 24; 18L	136
3	18R;18C | 24	10.76%	116	18R;18C | 24	135
4	18R; 18C | 18L	5.5%	95	18R; 18C | 18L	128
5	18R | 18L	5.5%	64	18R | 18L	91

Conclusion and Discussion

- MLA is promising to predict runway configuration
- Historical data relates the future runway configuration
  - Metrological conditions (METER and TAF)
  - Traffic distribution

- Future research:
  - Quantification of the influencing factors


Thank
you