A Predictive Aircraft Landing Speed Model Using Neural Network

Dr. Ousmane Diallo

NASA Ames Research Center
Moffett Field, CA

Outline

- Background & Motivation
- Modeling Methodology
- Application
- Results
- Summary & Future Work

Background & Motivation

Background: NextGen

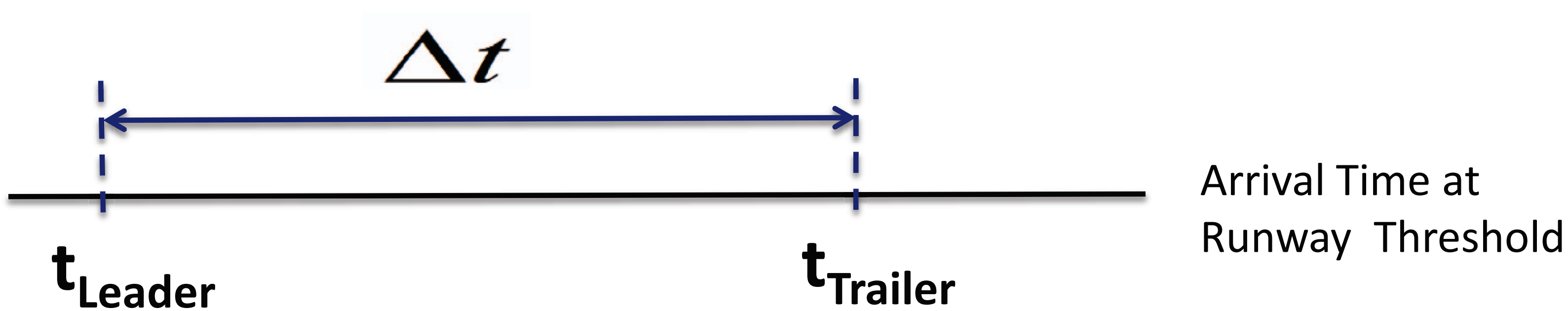
- NextGen is a plan to modernize the National Airspace System (NAS) by 2025

- One NextGen goal is to accommodate traffic increase in the already congested terminal area

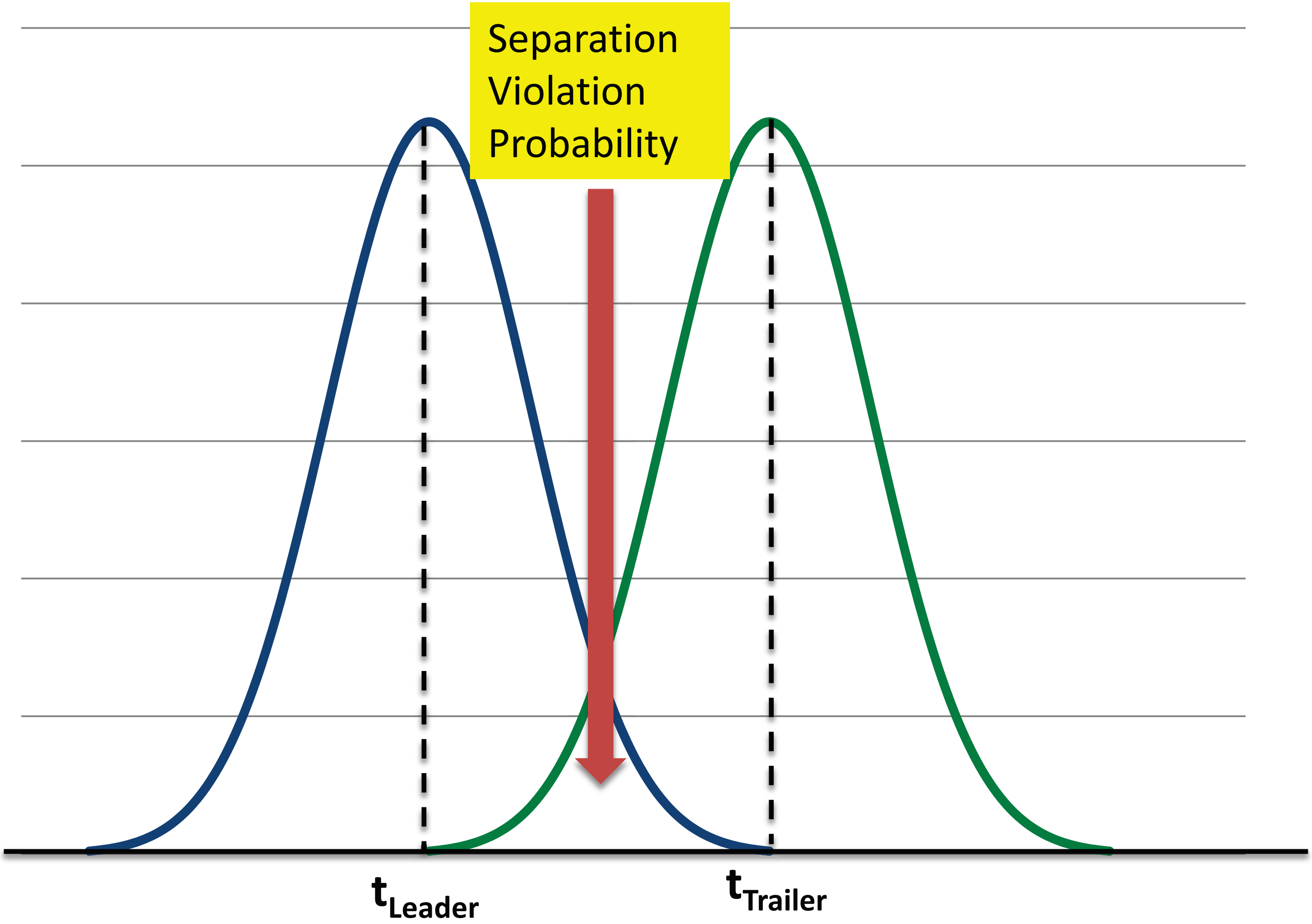
Motivation- Problem Statement

- One hurdle to increase throughput
  - Uncertainty of aircraft arrival time at runway threshold

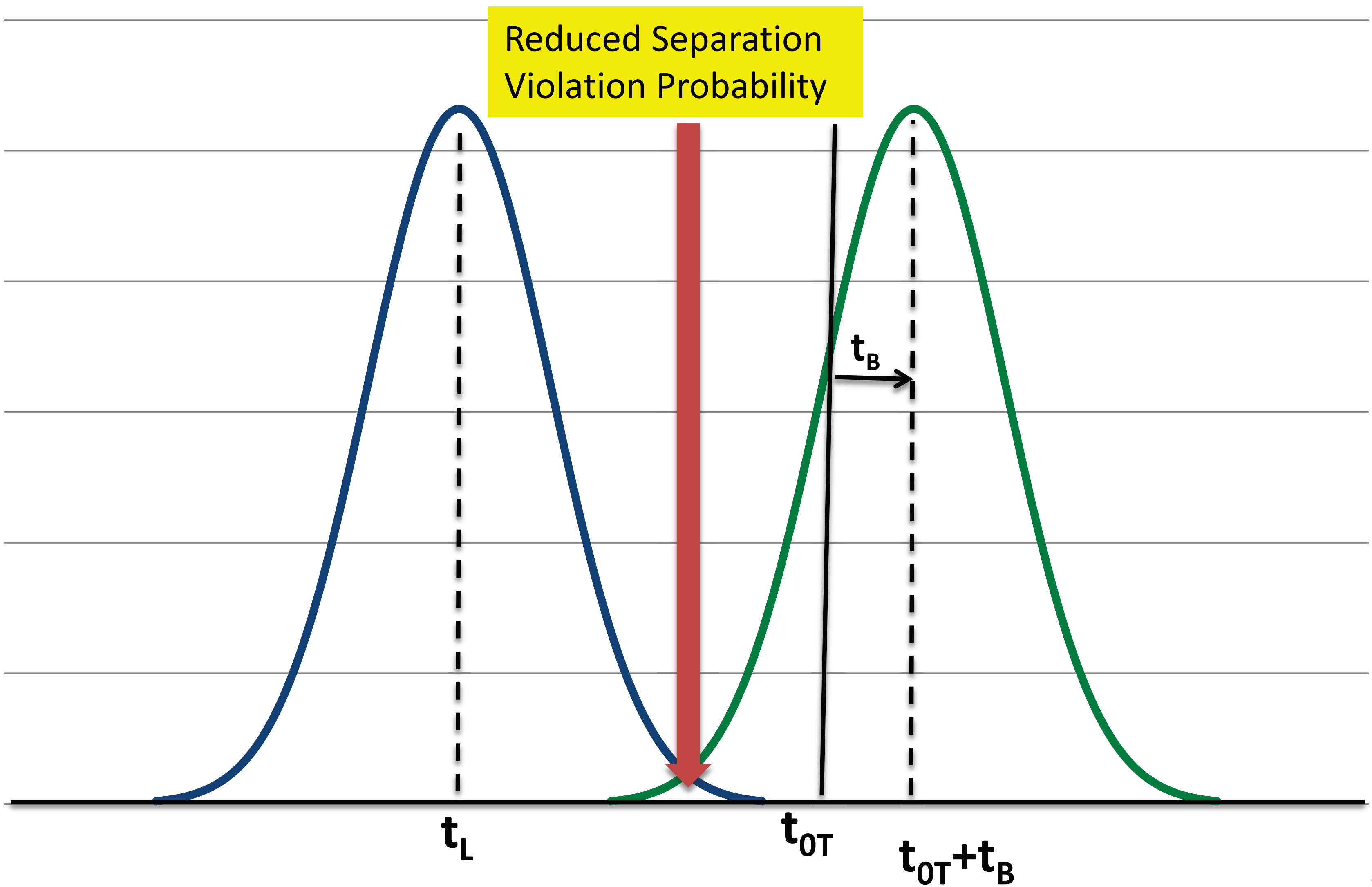
- Δt necessary to avoid separation Violation



Motivation - Problem Statement



Problem Statement – Current ATC Solution



Objective

To reduce the variance of the landing speed prediction error as much as possible

Potential Landing Speed Estimation Options

- Controllers can verbally request the landing speed from the flight crew and input it in an interactive tool
- The intended landing speed can be electronically communicated to controllers by the flight crew
- A model can be built to estimate the aircraft's landing speed.

Prior Research on Landing Speed Prediction

- Simplistic speed profile approximated landing speed with limited success

- Linear models provided acceptable prediction using large number of input variables
  - Poor prediction with reduced number of input variables

Modeling Methodology

Data Selection and Processing

- Data collection is conducted
  - Airlines-monitored flight parameters
  - Airport atmospheric condition
- A formal screening process is performed
- Final parameters selection decision is made
- Neural network model is built

Neural Network Model - Background

- Feed-forward NNs
  - Handle non-linear relationships
  - Easy to build and train
- Architecturally composed:
  - Input layer
  - Hidden layers
  - Output layer

Neural Network Model - Mathematics

- Hidden Nodes – the data processing center of the network:

$$H_j = S\left(d_j + \sum_{i=1}^{N} \left(C_{ij} X_i\right)\right)$$

- Logistic Sigmoid function scales input value between 0 and 1

$$S(z) = \frac{1}{1+e^{-z}}$$

Model Evaluation Metrics

- Target (baseline) Speed Error

$$Error_{V_{Target}} = \left(\frac{V_{Actual} - V_{Target}}{V_{Target}} \right) \times 100$$

- Model Prediction Error

$$Error_{V_{Model}} = \left(\frac{V_{Actual} - V_{Model}}{V_{Model}} \right) \times 100$$

Application

Scope of Study

- Over 300 parameters collected
- Down selection based on data availability and quality
- Dallas/Fort Worth Airport selected - has a field site infrastructure
- MD 80 Aircraft type selected- has the most flight samples

Current Published Procedures - Baseline

- Aircraft operating manuals provide landing speed recommendation for each aircraft type
- Recommendation to pilots for MD 80
  - Low gust condition landing (Gust <10 knots)

$$V_{Target} = V_{ref} + 5knots$$

  - High gust condition landing

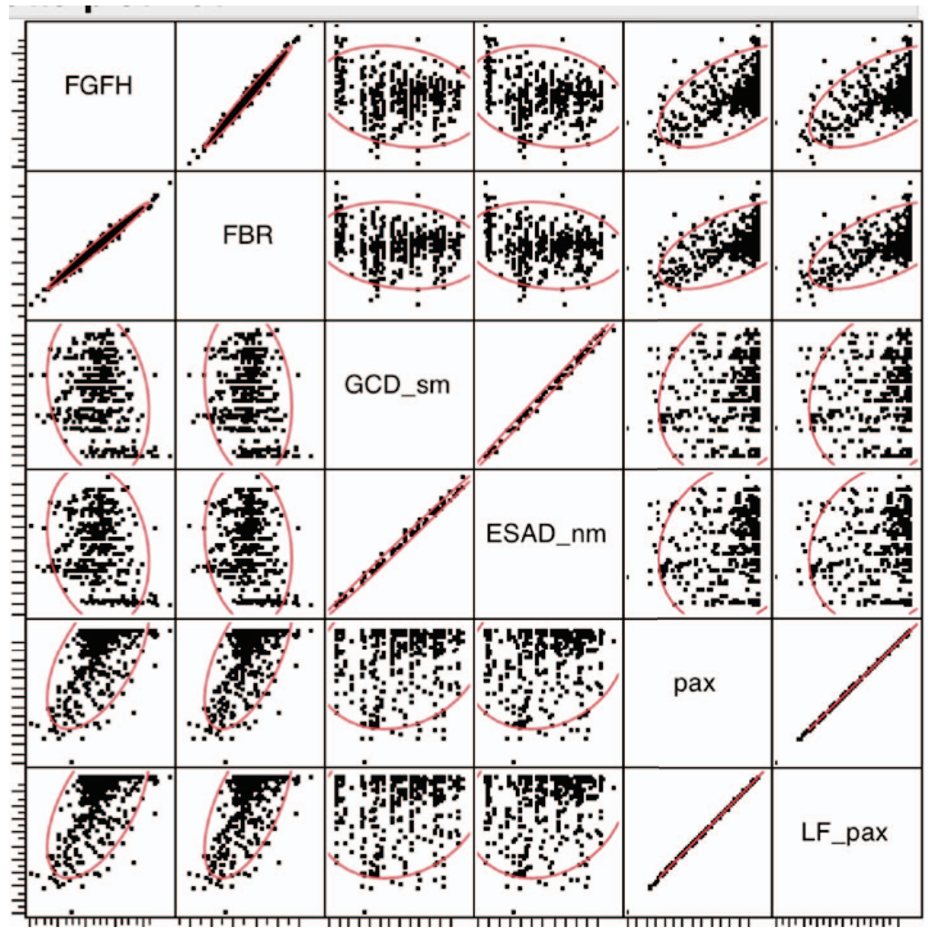
$$V_{Target} = V_{ref} + \frac{1}{2}SW + GW$$

With maximum additive wind not to exceed 20 knots

Data Selection & Screening Process

- Engineering irrelevant parameters are eliminated
- For variables that provide duplicate information, only one is used

NxN Correlation Matrix



Screening Results – 5 Variables

Parameter	Description
Head wind	Head Wind
Gust wind	Gust Wind
Ceiling_ft	Forecast Ceiling
Vis_ft	Forecast Visibility
Act_Land_Wgt	Actual Landing Weight

Neural Network Building

High Gust MSE plot

Mean Squared
Error (mse)

12 Epochs

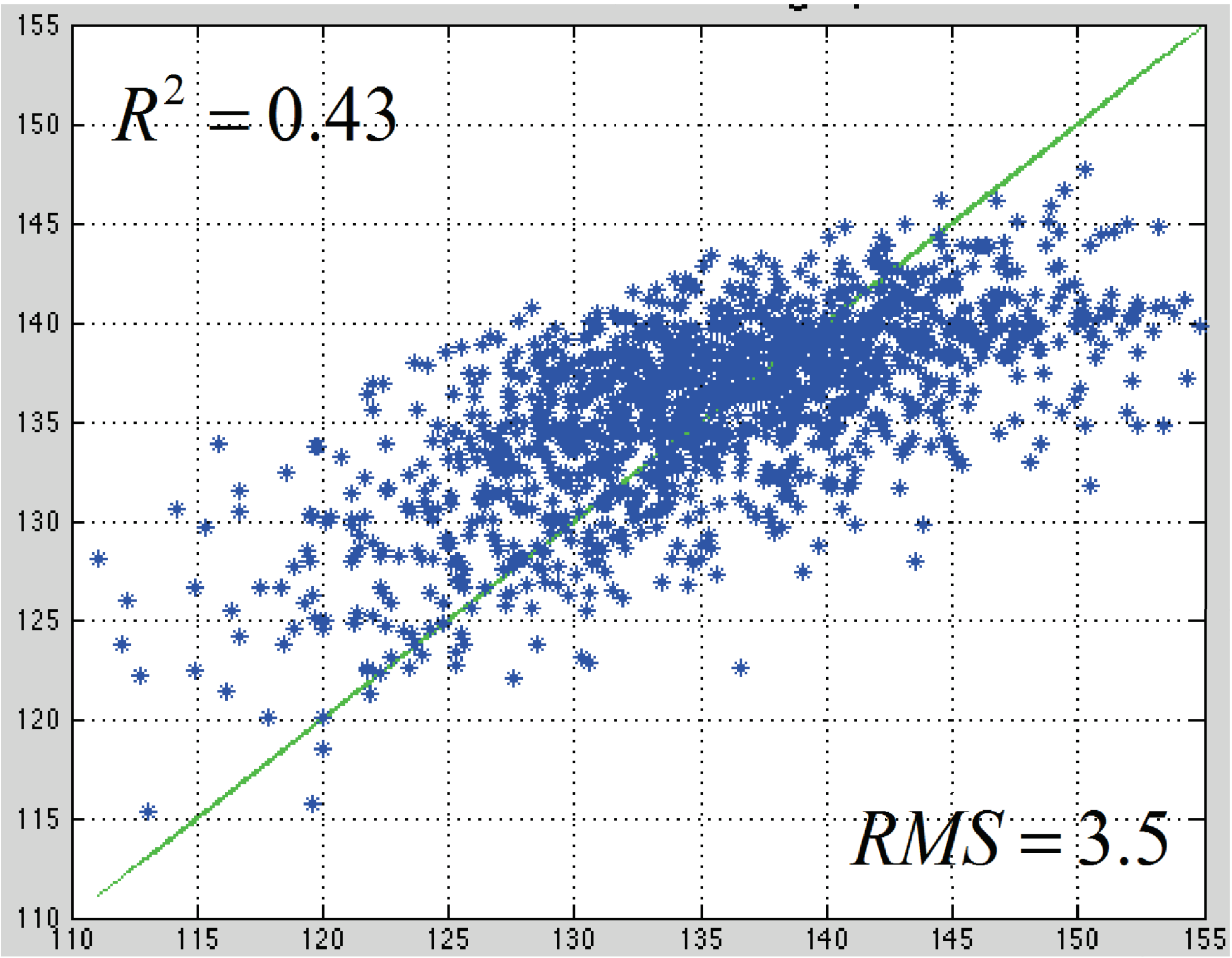
- Levenberg-Marquardt algorithm
- MSE performance function used as stopping criteria

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(e_i)^2 = \frac{1}{N}\sum_{i=1}^{N}(t_i - a_i)^2$$

- All 3 data sets converged

Quality of Fit of Low-and-no Gust Condition: Actual vs. Predicted Landing Speed

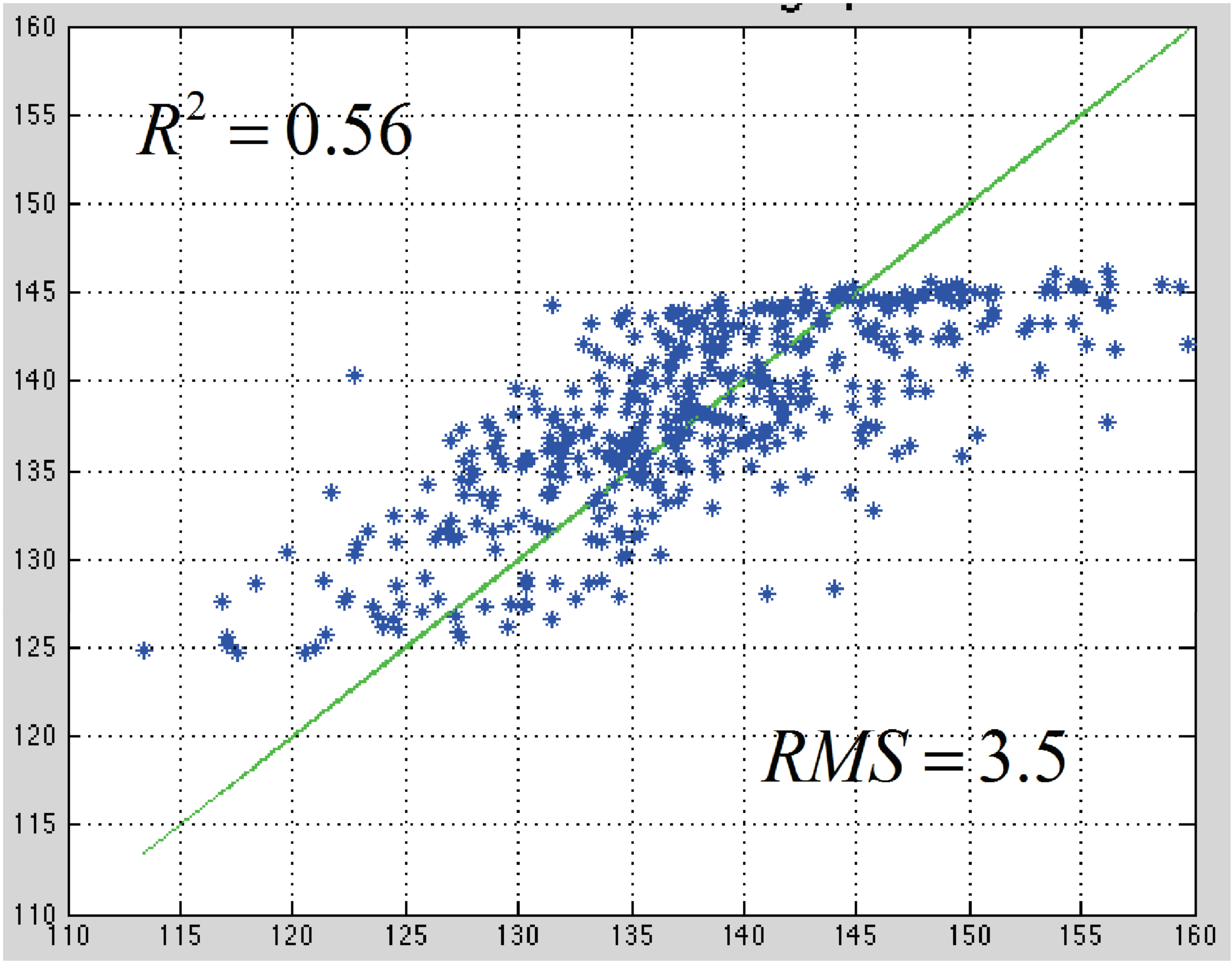
Actual Landing Speed (knot)



Model Predicted Landing Speed (knot)

Quality of fit of High Gust Condition- Actual vs. Predicted Landing Speed

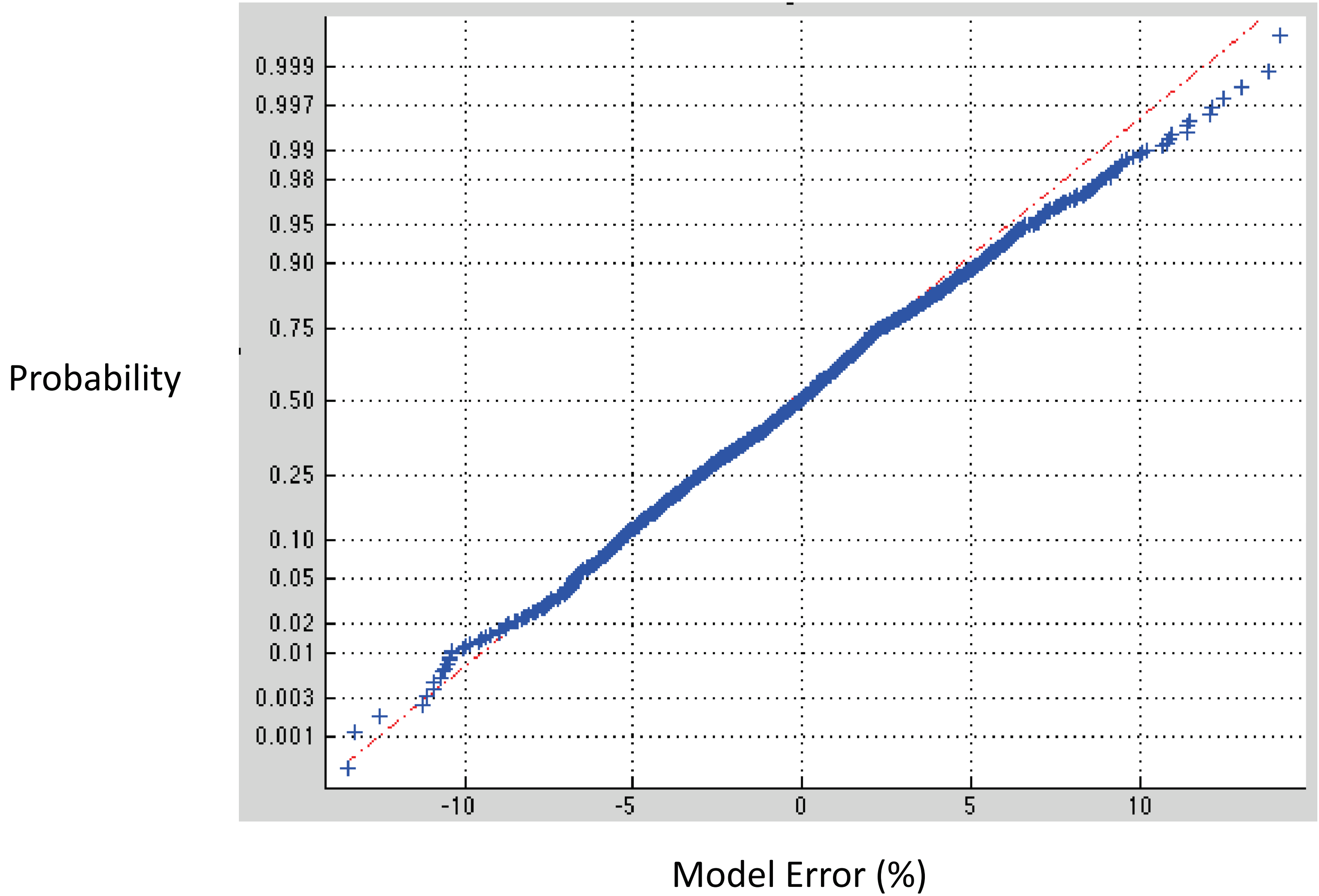
Actual Landing Speed (knot)



Model Predicted Landing Speed (knot)

Results

Landing Speed Error Characteristics – Normal Probability Plot for Model Error



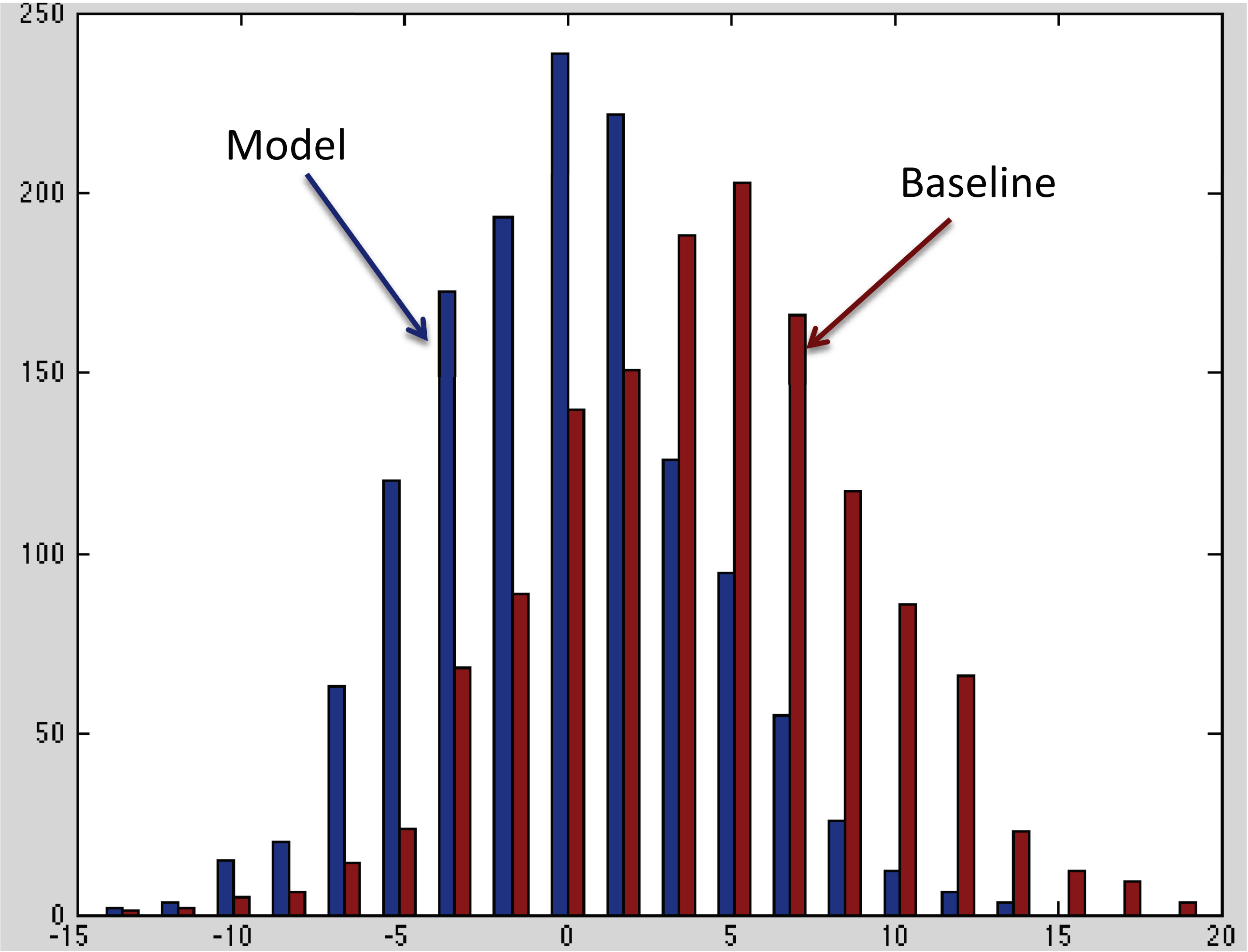
Model Performance – Error Statistics

Statistical Parameters	Low and No Gust Error		High Gust Error	
	Model	Baseline	Model	Baseline
Mean	-0.1	4.2	-0.2	-6.9
std Dev	4.2	4.9	4.0	4.4
Min	-13.5	-14.5	-12.5	-19.2
Max	14.2	19.6	13.4	7.6

- Models error mean values around 0
  - Indicate models are closer to actual landing speed compared to recommended landing speed error
- Models error standard deviation values smaller
  - Illustrate less dispersion compared to published procedures landing speed error

Low-and-no Gust Condition – Percentage Error

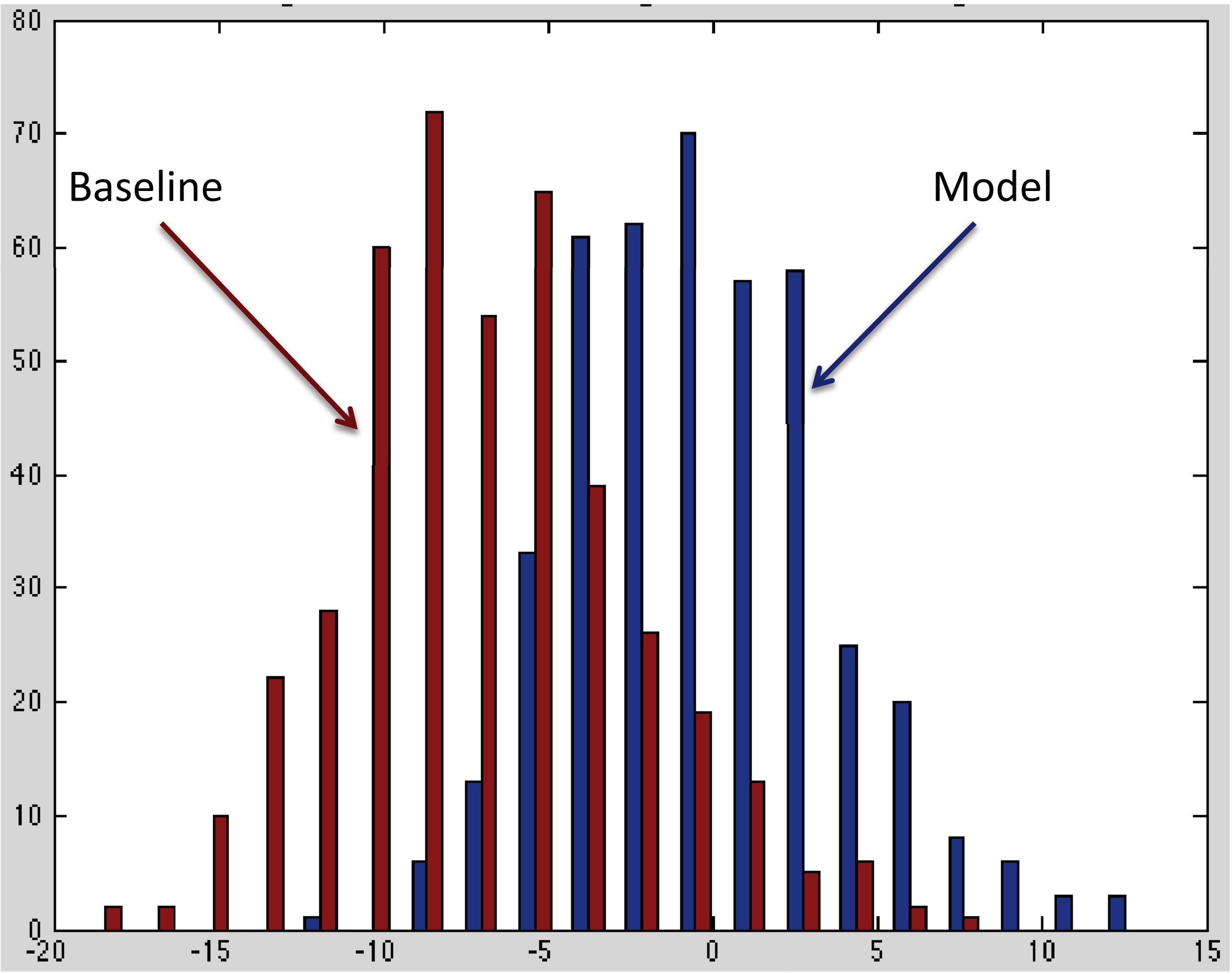
Number of Instances



Percentage Error

High Gust Condition- Percentage Error

Number of Instances



Percentage Error

Summary & Future Work

Findings

- Models Performances
  - 95% of landing speeds predicted within 12.6% error margin for low-and-no gust
  - 95% of landing speeds predicted within 12% error margin for high gust
- Uncertainty Reduction (at 3-sigma confidence level)
  - Reduces uncertainty of the prediction by 18% for Low-and-no gust condition
  - Reduces uncertainty of the prediction by 9.5% for high gust condition
- Other Findings
  - Pilots land at higher speed than recommended in the low-and-no gust condition
  - Pilots land at lower speed than recommended under high gust condition

Summary

- A Neural Network model based on limited variables is created

- Neural Network models predicted landing speed better than the published Pilots’ procedures
  - Accuracy Improved - Mean value for error is around 0
  - Precision Improved - Standard deviation value for model is at least 10% smaller

Future Work

- Accuracy of model can be improved
  - Other impactful parameters may be missing from analysis
  - More fine tuning of parameters may be needed
- Model other airports and aircraft types
- Integrate pilots' behavior into the prediction

Thank-you!

Ousmane N. Diallo
ousmane.diallo@nasa.gov