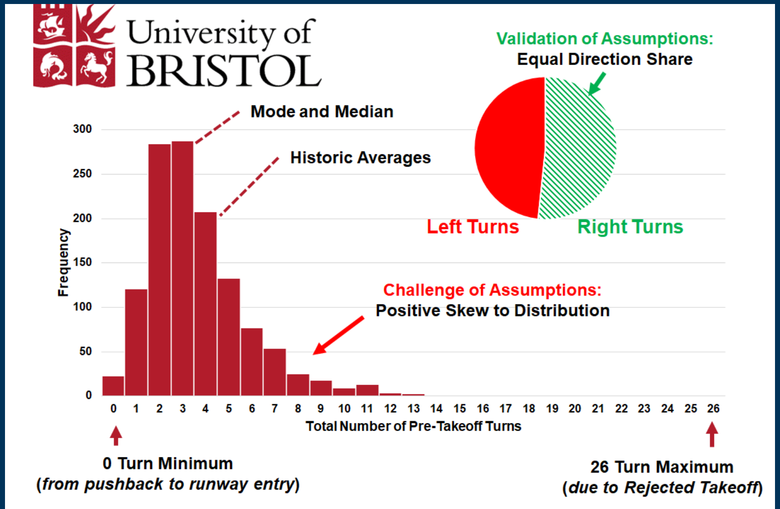
HBM Prenscia Technology Day

Virtual Seminar Series



Exploiting Novel Data Sources in Probabilistic Design

Presented by Dr. Josh Hoole
Research Associate, Electrical Energy Management Group
University of Bristol

Session #5: Mathematical Modelling for
Data Analytics, Durability, and Reliability #1

Exploiting Novel Data Sources in Probabilistic Design

Abstract

Probabilistic design approaches provide a route to assessing the reliability of safety-critical structures, potentially yielding more optimum designs, increased service lives or a quantification of the level of safety within a structure. However, one of the inhibiting factors that routinely prevents the implementation of probabilistic approaches is the lack of available data to statistically characterise the variability present within engineering parameters. Fortunately, the rapidly growing field of 'big-data' now provides greater opportunities for capturing engineering design datasets than ever before. This presentation will demonstrate a novel data source, in the form of real-time aircraft tracking, which has been exploited within the development of a probabilistic fatigue methodology for aircraft landing gear structures.

About the presenter, Dr. Josh Hoole

Josh is a research associate based in the Faculty of Engineering at the University of Bristol. Josh's research focuses on the development of statistical and probabilistic methodologies for engineering design and assessment. One of the specific aims of this research is to make probabilistic approaches more practical and accessible within industrial design processes and analysis workflows. Whilst working in the Department of Aerospace Engineering at the University of Bristol, he participated in the Aerospace Technology Institute funded "Large Landing Gear of the Future" project in collaboration with Safran Landing Systems. Currently, Josh continues to conduct probabilistic-focused research within the university's Electrical Energy Management Group (EEMG).

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Exploiting Novel Data Sources in Probabilistic Design

Dr Josh Hoole

Research Associate, University of Bristol

Presentation Outline

- A probabilistic approach to **fatigue design** of landing gear
- The **need** for novel data sources in probabilistic fatigue design
- The **exploitation** of novel data sources in probabilistic design
- **Lessons learned** from novel data sources

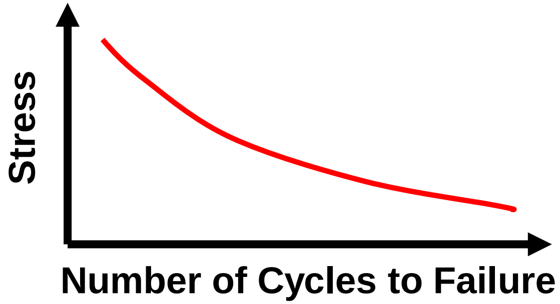
Landing Gear Fatigue Design Context

- **Landing Gear Components:**
  - **Safety Critical and Single Load-Path.**
  - **Large cyclic loads from ground manoeuvres.**
- **Safe-Life Philosophy:**
  - **Retire/overhaul at specified number of flights.**
  - **Classical S-N analysis supported by full-scale tests and safety factors.**

Safe-Life Fatigue Design of Landing Gear

Materials Data

- S-N Curve



Loads Data

- Load Spectra
- Load-Time History

Component Geometry

Stress Analysis

Cycle Counting

Stress Cycles

Number of Cycles to Failure

Miner's Rule

Accumulated Fatigue Damage

Safe-Life substantiation supported by:

- Safety Factors
- Full-scale Test

A Probabilistic Approach to Fatigue Design

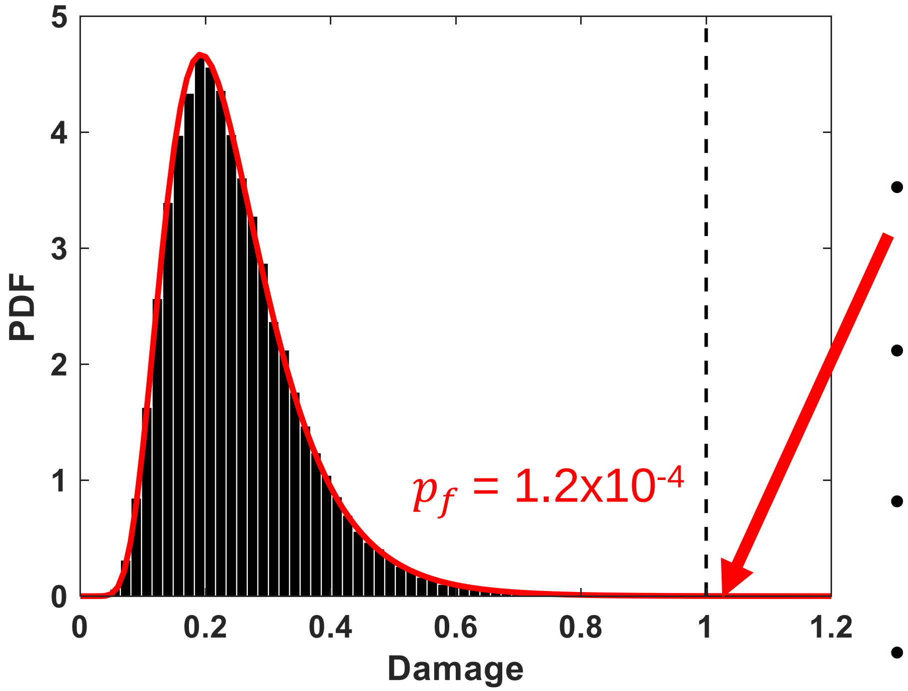
- Variability is present in fatigue design parameters.
- Propagates to variability in accumulated damage.

Component Properties:
- Component Dimensions

Material Properties:
- Static Properties
- Variability in S-N Data

Component Loading:
- Ground Manoeuvre Occurrence
- Manoeuvre Sequence
- Loading Magnitude

Safe-Life Fatigue Analysis
- Stress Life Approach and Miner's Rule



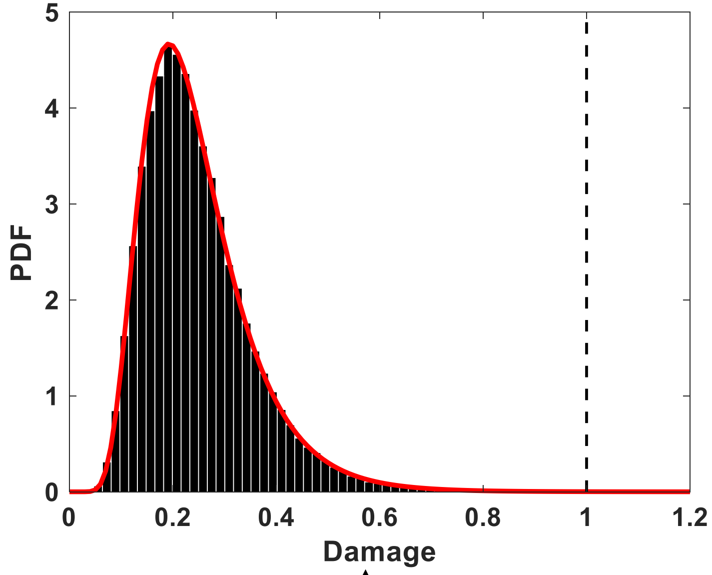
- **What is the probability of exceeding failure criterion at component safe-life?**
- **Step 1:** Characterise design parameters as probability distributions.
- **Step 2:** Propagate variability through existing analysis process.
- Probabilistic approaches have been previously developed[1].

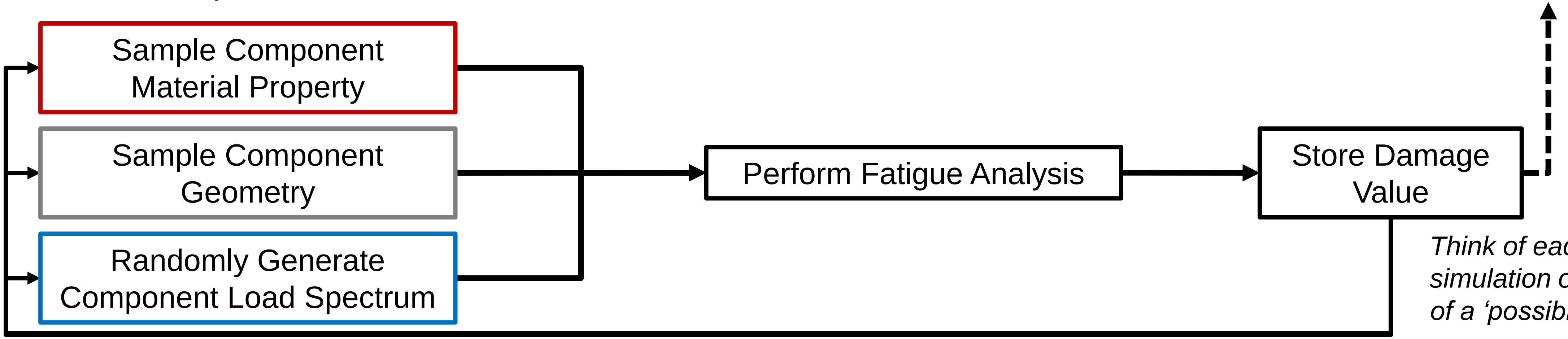
[1] Ocampo, J., et al, "Development of a Probabilistic Linear Damage Methodology for Small Aircraft", *Journal of Aircraft*, **48**(6), 2011, 2090-2106.

The Architecture for a Probabilistic Approach

A **Monte Carlo Simulation** is the simplest possible approach:

1. **Randomly sample** values for each engineering/design parameter.
2. Execute existing analysis process '***as-is***', using sampled values.
3. Store output and repeat for **many iterations**.
4. Estimate probability of failure based upon observed variability in output value.





Think of each iteration as the simulation of a complete life of a 'possible' component.

Fatigue Design: The Data *Landscape*

LOADING

Historically:
- In-service monitoring required direct instrumentation of structure.

Today:
- Real-time monitoring of structures, 'digital-twins', etc.

"Historically" is only 5-10 years ago…

Every element of fatigue design and analysis has seen an **increase in potentially exploitable data**.

MATERIAL PROPERTIES

Historically:
- Limited testing of material coupons.

Today:
- Stochastic modelling of materials (e.g. additive manufacturing).

FATIGUE DESIGN (*in general*)

COMPONENT PROPERTIES

Historically:
- Inspection of completed component.

Today:
- Data generation throughout manufacturing process (Industry 4.0).

Fatigue design provides an **ideal proving ground** for probabilistic and data-driven approaches due to its **inherent variability**.

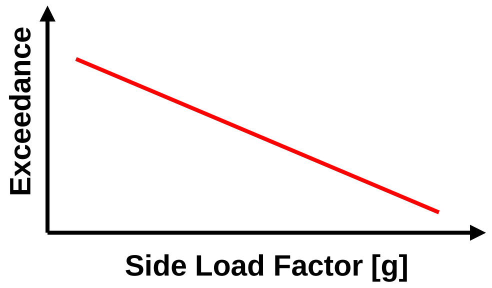
Landing Gear Loads for Fatigue Design

Existing practice for constructing landing gear **load spectra**:

Aircraft Mass

Magnitude

Load factor for each ground manoeuvre.



Blocking of exceedance curves

Landing Gear Loads for Fatigue Design

Assumed sequencing of ground manoeuvres

Occurrence

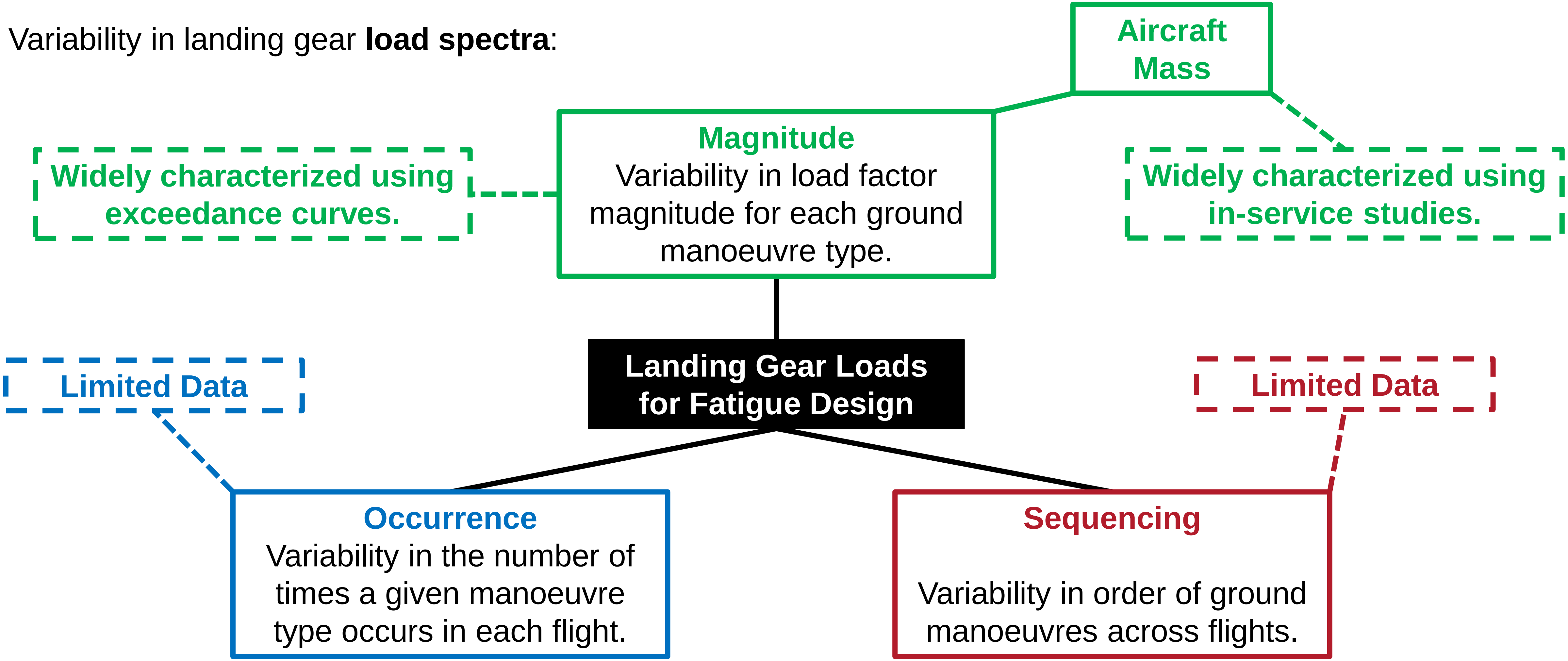
Number of ground manoeuvres performed.

Sequencing

Order of ground manoeuvres performed.

Variability in Landing Gear Loads

Variability in landing gear **load spectra**:



Manoeuvre Occurrence and Sequencing Variability

Variability in manoeuvre occurrence and sequencing is a direct result of **aircraft taxi routes**:

Taxi routes are dictated by a **large number of factors**:

- Departure and arrival airport.
- Airport geometry and aircraft compatibility.
- Weather (active runway direction).
- Airport traffic and local air traffic control procedures.
- The operator's typical gate locations
- *Etc…*

Significant **variability** in manoeuvre **occurrence** and **sequencing**.

- Assumed manoeuvre sequence currently required.
- Previous studies only consider **average** values of manoeuvre **occurrences**.
- **Limited to no data** regarding variability in manoeuvre **sequencing**.

Manoeuvre Occurrence and Sequencing Variability

1. More data is required to **better characterise** the variability in occurrence and sequencing of ground manoeuvre on a **per-flight basis**.

2. Improved characterisation would **permit existing practice** and assumptions to be **challenged** in order to ensure they are not either over- or under-conservative.

3. Fatigue analysis is reliant on **cycle counting methods** (e.g. ‘rainflow counting’). Results from rainflow counting are **sensitive to the sequence** of load/stress levels.

4. **Probabilistic-based approaches** would require data regarding manoeuvre occurrence and sequencing variability.

LESSON #1:

The big-data ‘boom’ is not limited to world of structural health monitoring or digital-twins. It can **feedback into our existing design process.**

Data Collection Aim / Target Statistics

What data is **required to support** the objectives on the previous slide?

Occurrence of turning manoeuvre and direction per-flight:

Occurrence of braking/deceleration manoeuvre per-flight:

Is there an equal share between turn directions?

Is there a difference between pre-takeoff and post-landing taxi phases?

Is there a correlation between number of turns and number of braking actions?

Occurrence of 'milestone' manoeuvres per-flight:

- *Pushback direction.*
- *Runway entry type and direction.*
- *Runway exit type and direction.*
- *Turn onto stand direction.*

Sequencing of manoeuvres –
the probability of a given manoeuvre occurring after :

- *A turn of a given direction.*
- *A braking/deceleration manoeuvre.*

LESSON #2:

Clearly establish what you need to extract from the dataset.

Ask the right questions and know your existing limitations.

Introduction to ADS-B Data

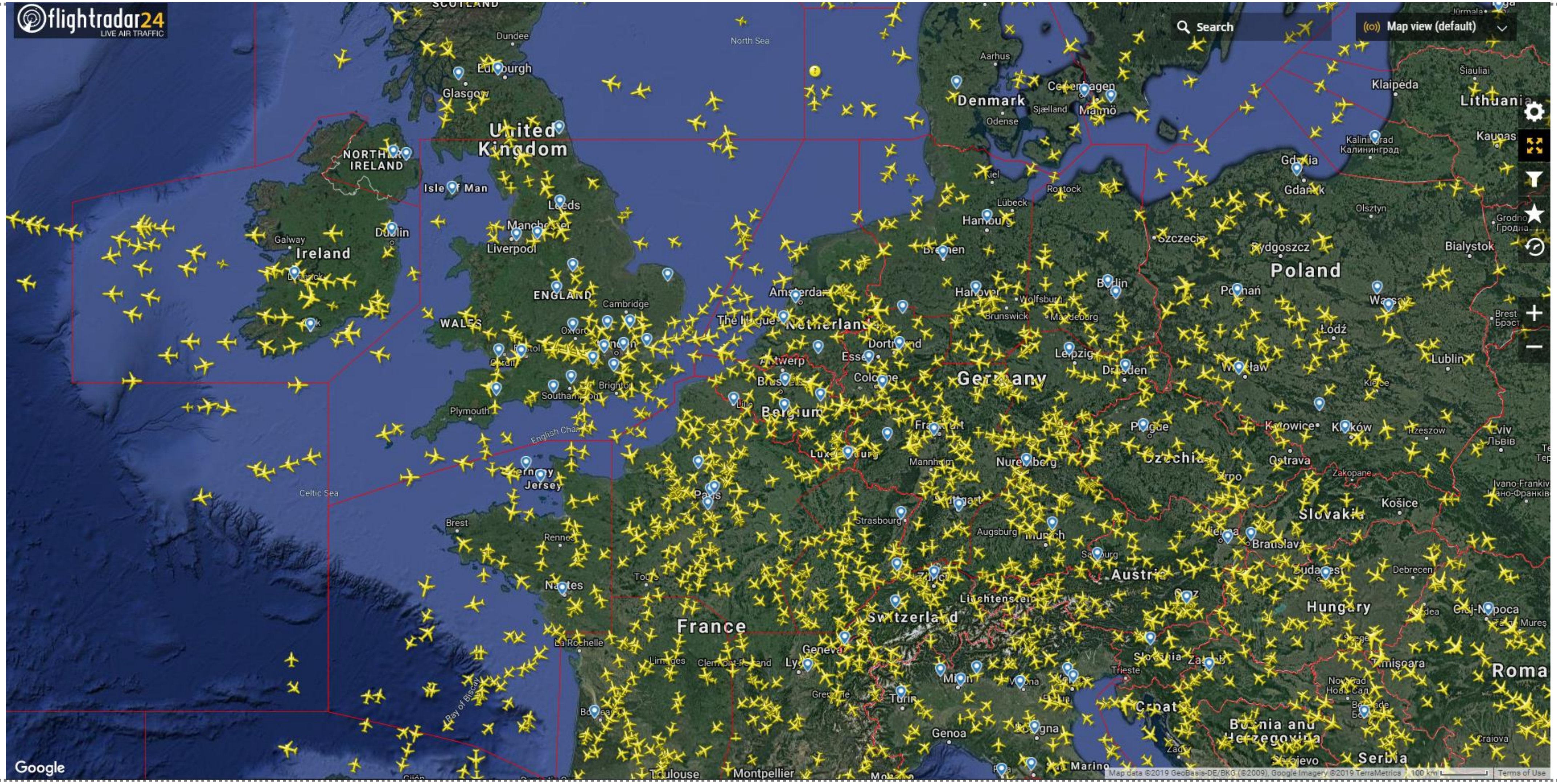
In the '**digital age**' of the aerospace industry, **real-time tracking** of aircraft is a real possibility.

Automatic Dependent Surveillance-Broadcast (**ADS-B**) Transponders provide key **flight parameters** when **interrogated** by a ground station:

- Callsign/Aircraft Registration.
- Aircraft speed.
- Altitude.
- Heading.
- Location in Latitude/Longitude.

ADS-B coverage across aircraft **types**, majority of **operators** and **locations** across the globe…

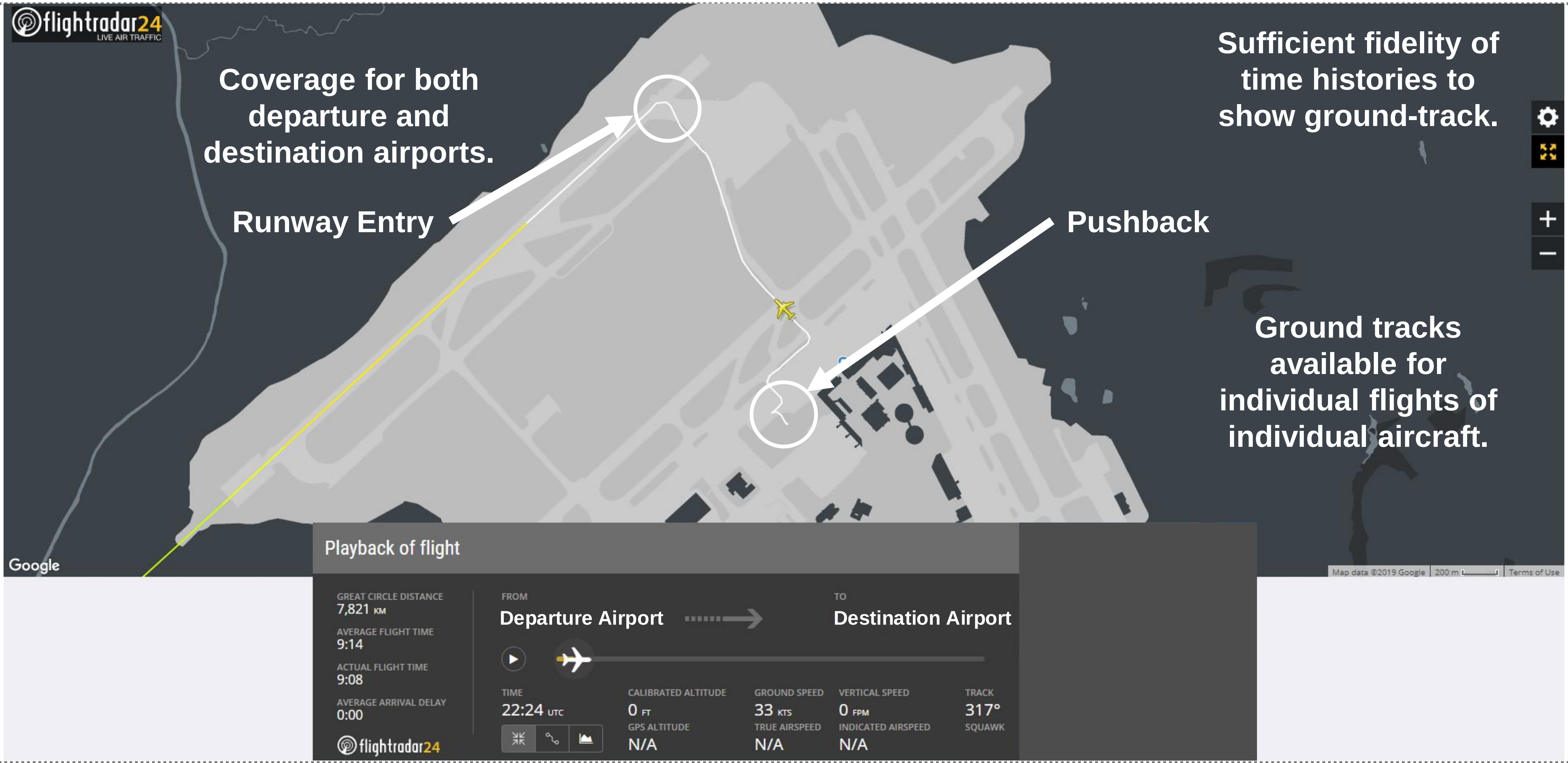
Introduction to ADS-B Data



Screenshots from:
https://www.flightradar24.com/

Utility of ADS-B Data

17th November 2020



Screenshots from: https://www.flightradar24.com/

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Format of ADS-B Data

17th November 2020

Behind the user interface and ground tracks, a simple and **raw ADS-B data file** is available for **each flight**:

Timestamp	Callsign	Latitude	Longitude	Altitude [ft]	Speed [kn]	Heading [deg]
1521427454				0	2	87
1521427529				0	0	139
1521427684				0	0	65
1521427809				0	2	87
1521427828				0	14	84
1521427848				0	17	81
1521427856				0	19	78
1521427863				0	20	78
1521427873				0	20	78
1521427880				0	20	78
1521427886				0	19	78
1521427899				0	17	92
1521427912				0	17	126
1521427922				0	14	151
1521427929				0	15	163
				0	19	168
				0	21	168
				0	21	168
				0	18	160
				0	17	120
				0	16	87
				0	17	78
				0	19	78

Redacted for Sensitivity

LESSON #3:

Know your data.

What trends already exist?

Overall Data Collection Approach

1. Production of a series of **simple conditional statements**, that interrogate the ADS-B data files row-by-row to identify:

   - **Heading changes** to record turning manoeuvres.
   - **Speed changes** to re

2. Additional conditional state ... nway entries/exits and Turn ont

LESSON #4:

Keep it simple.
(Although this isn't always possible)

3. Storage of the **sequencing of the manoeuvres** for each flight.

4. Counting or '**tally**' of the number of manoeuvres of a given type within a flight, and a tally of the type of manoeuvres following a given manoeuvre (for sequencing).

[2] Hoole, J., et al, "Landing Gear Ground Manoevure Statistics from ADS-B Transponder Data", The Aeronautical Journal– UNDER PEER REVIEW.

Setting-up the Dataset

A wide-body passenger airliner was selected for this study.

1,200 flights randomly selected from across this potential dataset.

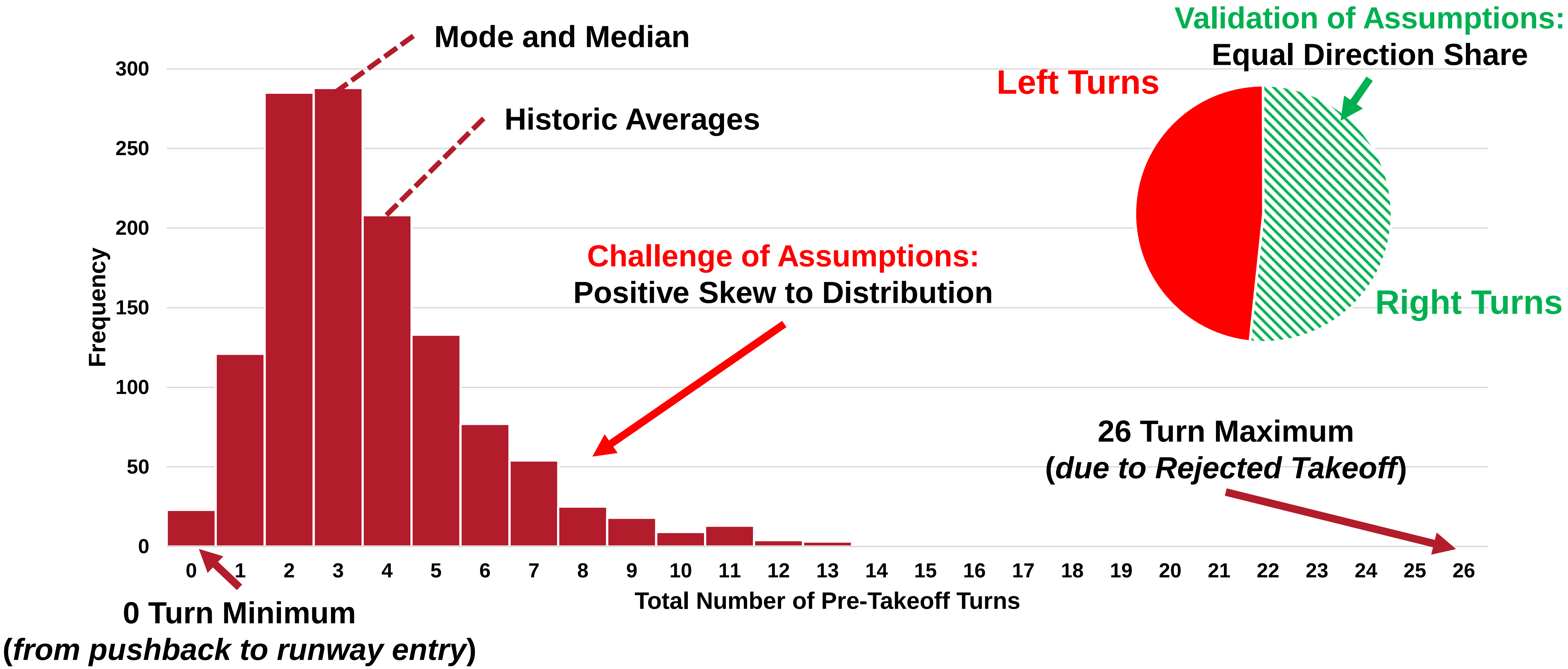
Potential dataset could be aggregated across a year for the entire **global fleet**.

Application of algorithms generated **30+** ground manoeuvre **statistics**.

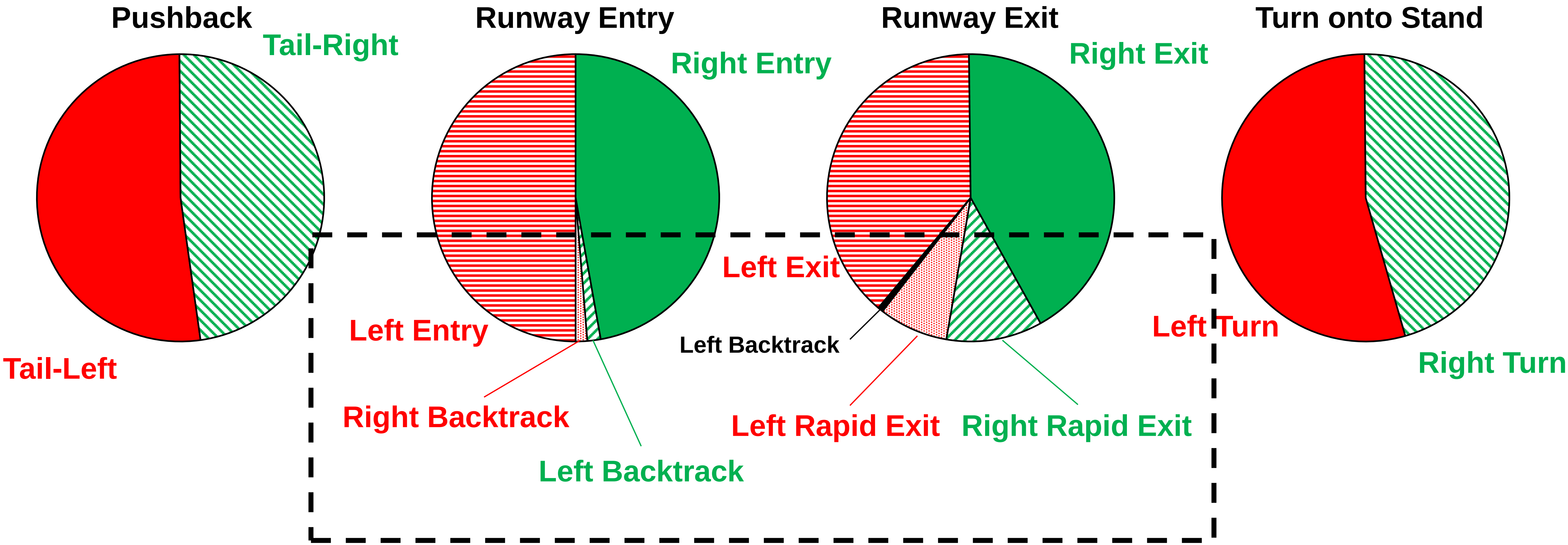
LESSON #5:

Even simple data collection/analytics can lead to having far more detail to capture within your design/analysis approach.

Example Results #1

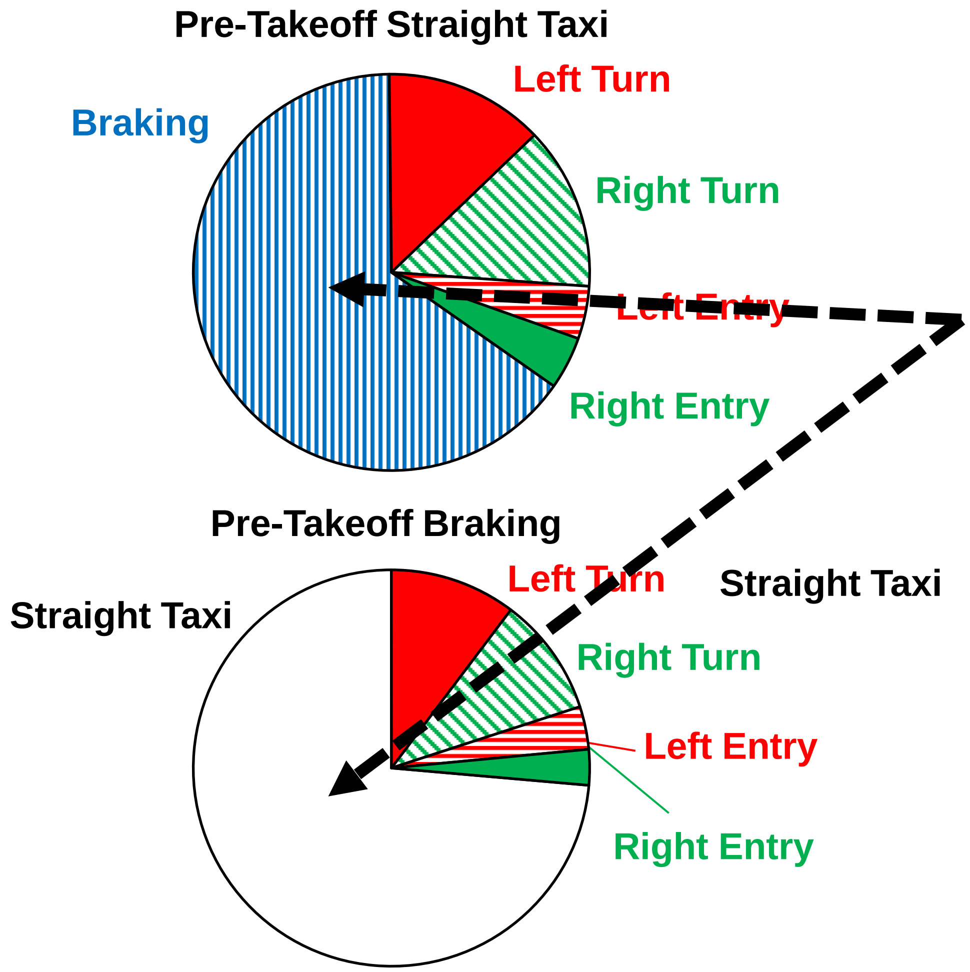


Example Results #2



We care about the probability of each of these different types of runway entry/exit occurring within a probabilistic approach because they result in different loading on the landing gear.

Example Results #3



- This is where novel data sources have broken “new ground” – to date manoeuvre sequence statistics have **not been available**.
- Statistics recover known aircraft operational **behaviours** e.g. ‘queuing’…
  - …hence, within a probabilistic approach we can begin to build fatigue spectra that accounts for these known ‘behaviours’…
  - … and we ultimately end up with a fatigue analysis which is **more representative of reality**.

Verification

- **10% of flights** randomly selected.
- Identified manoeuvres and sequence for each flight **compared with FlightRadar24® ground track:**

Verification Task	Accuracy
Complete Flight Correct	**47.7%**

LESSON #6:

Know the limitations of your data source/datasets and the limitations of your methods.

(what might be acceptable and useful in one application may not be in another…)

- Error in **pushback identification** would **propagate** through manoeuvres sequence.

The Exploitation of Big-Data Sources

- The key thing to remember is that a load spectrum is a ***simulation*** of a component design-life…

- …and a probabilistic approach aims ***simulate*** the variability…

- …this novel data source therefore provides the required data to **statistically simulate** aircraft flights.

- We can then push this captured variability in loading through the fatigue analysis process, using a **whole host of probabilistic methods** (e.g. Monte Carlo Simulation).

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Conclusions and Lessons Learned

- Whilst this presentation has considered an aerospace application, ‘big-data’ and novel data sources are occurring ever more frequently in all sectors of engineering, so what are the take-home **lessons**?

#1 Do not miss the opportunity to **feedback** new data into existing design/analysis processes.

#2 Clearly establish what you aim to get **out** of your data source – *what is important?*

#3 Work with your dataset before applying any methods – *what **trends** and limitations does it have?*

#4 Where possible, keep the statistical/data analysis techniques as **simple** as possible.

#5 Be prepared for new data sources to increase the **complexity** of your existing processes.

#6 Know the **limitations** of your data source and methods – *verify and validate where possible.*

This presentation represents work performed as part of the Aerospace Technology Institute (ATI) funded "Large Landing Gear of the Future" project in collaboration with Safran Landing Systems.

Thanks to FlightRadar24® for providing permission to reproduce ADS-B data and screenshots with this research.
https://www.flightradar24.com/

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https://research-information.bris.ac.uk/en/persons/joshua-hoole

Q&A

- Prashant Khapane (Jaguar Land Rover, UK)
  - Hi, Thanks for the interesting presentation. I do agree that loads are probabilistic and not deterministic. What do you think about how we could use the data/trends for the large loads encountered during landing and braking manoeuvres?
    - *The variability present in the loading magnitude associated within specific manoeuvres has been well characterised from previous in-service monitoring campaigns. However, other researchers within this area have begun to derive aircraft performance metrics based on this data source. Therefore, the wider exploitation of ADS-B data sources within aerospace design will continue to grow, especially as such methods provide visibility across the global fleet of a given aircraft type.*

- Wasim Shaikh (John Deere, India)
  - In areas such as construction equipment, where there is huge variation in the usage pattern and lack of knowledge about machine learning algorithms, how can we use this method?
    - *The key idea when trying to extract usage variation is to understand a) your available data, b) what are your 'quantities of interest' you want to extract from the data source and c) how patterns within this data reflect the quantities of interest within the usage pattern. An example data source from construction equipment could be on-board diagnostic information. A lot can be learnt from studying a limited number of target items of equipment/vehicles in detail to help establish the relationship between usage events. This then allows the conditional "IF" statements to be constructed to extract the usage events from the datasets. This will ultimately build a bespoke set of simple algorithms that extract usage events. Regarding the future implementation of machine learning methods, such approaches are becoming ever more user-friendly and hence the 'learning-curve' to using such methods is rapidly decreasing.*

Q&A

- Muhammad Afzal (Omnicell, USA)
  - What's the cut off small data vs. big data?
    - *The difference between small data vs. big data will vary between sectors, industries and applications. Within the context of this work, the data source has the potential to be a big data source, although only a small subset of the available data was considered. Within aerospace design, real-time aircraft tracking can be considered 'big' as historically the sector has had to rely on the specific monitoring of only a few individual in-service aircraft.*
- Anonymous
  - Beyond the challenge of data being available to support probabilistic design, what other blockers are there that prevent such approaches being used more widely within the engineering industry?
    - *There are two key factors that limit the wider implementation of probabilistic approaches within engineering. Firstly, the additional required statistical knowledge is often considered as a significant resource burden and therefore, improved methods and tools for communicating statistical techniques are required. However, the greatest challenge concerns design/acceptance criteria. The long established practice of designing to safety factors means that reliability targets are not available for many sectors and applications. For probabilistic approaches to be used in day-to-day engineering practice, the definition of acceptable structural reliability targets is required.*
- Anonymous
  - Concerning novel data sources, especially those falling into the category of 'big-data', what do you see as the greatest challenge when working with such data sources?
    - *The greatest challenge is defining the 'scope' of what you wish to extract from the data. It is often tempting to extract as much information from such data sources as possible, although this can result in too much information to process and incorporate into existing design practices. The best way to define the scope of your data analysis activities is to firstly identify the areas of the design process in which the existing available data is deficient.*

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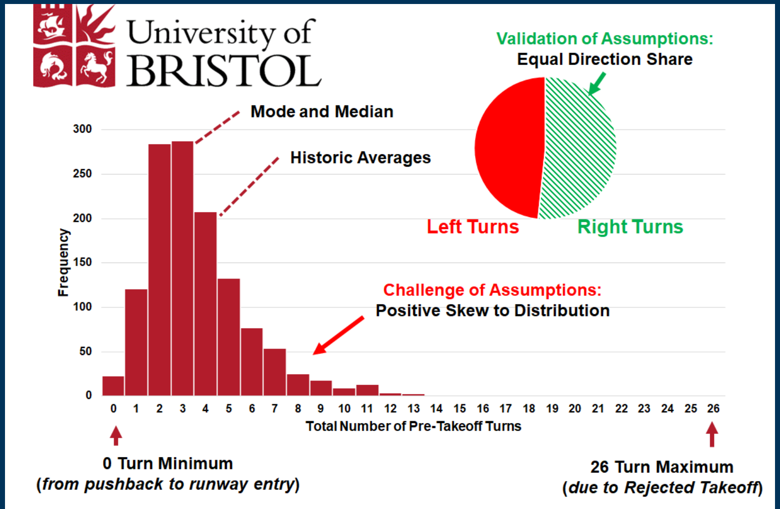

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