PEGASAS Project No. 2
Rotorcraft Aviation Safety Information Analysis and Sharing (ASIAS)

Presented by

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Although the FAA has sponsored this project, it neither endorses nor rejects the findings of this research. The presentation of this information is in the interest of invoking technical community comment on the results and the conclusions of the research.

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Sophrodyne aerospace · Robinson Helicopter Company · Loft Dynamics · ART · Airbus Helicopters · Vuichard Recovery Aviation Safety Foundation

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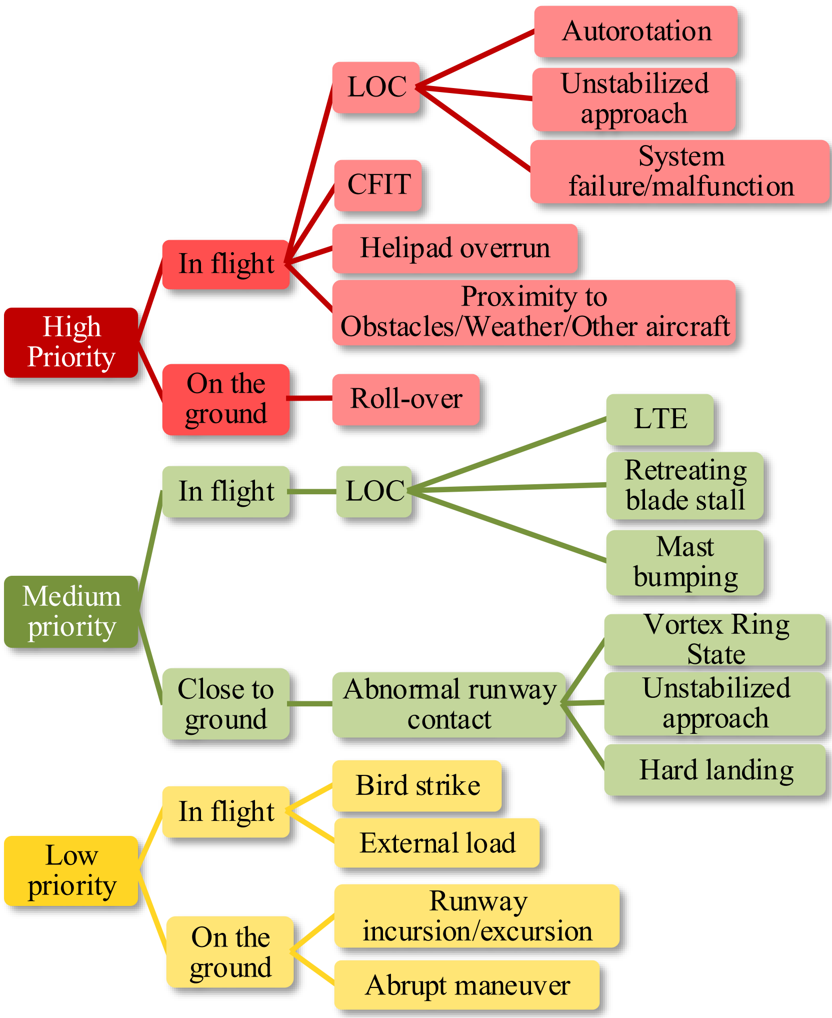
Alexia Payan, PhD

Executive Summary

- Motivation and Objectives
- Concept of Operations
- Rotorcraft Mission Segments
- Data Analysis for Safety
  - Flight Simulation for Vortex Ring State Training
  - Dynamic Rollover Study
- Conclusions and Future Work
- Publications and Accomplishments

Flight Data Monitoring

- Flight data collection and proactive risk mitigation analysis of ordinary flight operations is known as **Flight Data Monitoring (FDM)**
- FDM programs are one of the most widespread safety programs for **rotorcraft safety**
- An FDM program consists of:
  - Collecting flight data
  - Developing safety analysis tools/techniques
  - Enabling risk mitigation efforts
- The power of FDM is shown via **safety metrics** which detect hazardous flight conditions
- **Safety metrics** help pinpoint **anomalies** and **deviations** from standard operating procedures before they become incidents or accidents



What is Aviation Safety Information Analysis and Sharing (ASIAS)?

Aviation Safety Information Analysis and Sharing (ASIAS)

A **collaborative government** and **industry** initiative on **data sharing** and **analysis** to **proactively discover safety concerns** before accidents or incidents occur, leading to **timely mitigation** and **prevention**

ASIAS = Continuous Improvement in Aviation Safety

Alexia Payan, PhD

Rotorcraft Aviation Safety Information Analysis and Sharing (ASIAS)

Voluntary submission of safety-sensitive data

Procedures & policies based on **collaborative governance**

Operator/OEM/MRO **data are de-identified**

Analyses **approved by** an **ASIAS Executive Board**

Transparency on how data is managed and utilized

Data used solely for **advancement of safety**

Rotorcraft Mission Segments in ASIAS

Air Tour

External Load

Airborne Law Enforcement

Aerial Firefighting

Search and Rescue

Helicopter Air Ambulance

Training

Offshore

Corporate/VIP Transport

HFDM Research for ASIAS

__Goal__: Support the USHST efforts to reduce the helicopter fatal accident rate and thus improve rotorcraft flight safety by developing new analytical tools designed for the unique nature of helicopter operations

__Means__: Create integrated and secure rotorcraft flight data repository and safety analysis capability for broad use by rotorcraft operators to support creation of helicopter flight data analysis within ASIAS



DEVELOPMENT OF SAFETY METRICS FOR ROTORCRAFT OPERATIONS

FLIGHT SIMULATION FOR VORTEX RING STATE TRAINING

Vortex Ring State (VRS) – Overview of the Phenomenon

VRS inducing characteristics:

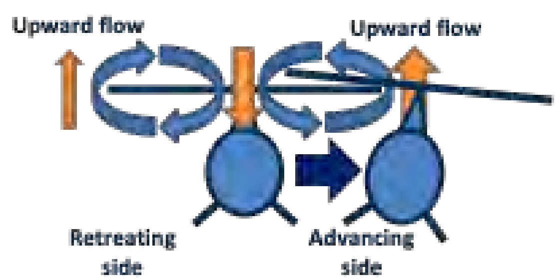
- Low or **zero true airspeed**
- Collective input creating induced flow
- **Sufficient Rate of Descent**, depending on the Helicopter disk loading

Symptoms of VRS encounter:

- **Increasing rate of descent**
- Random uncontrolled pitch, roll, and yaw
- Aircraft vibrations and stick shake
- Less control authority

Traditional Recovery Technique

Vuichard Recovery Technique



Power-Assisted Recovery Technique

Overview

There are currently **no objective, quantifiable requirements** for Helicopter Flight Simulator's performance and accuracy in **VRS entry and recovery** in the FAA and EASA qualification standards.

Flight Simulator Fidelity Assessment for VRS training

VRS Onset Evaluation:

Develop and apply a method to assess the fidelity of flight simulators for **VRS onset**

VRS Recovery Evaluation:

Develop and apply a method to assess the fidelity of flight simulators for **VRS recovery techniques**

Application

VRS Accident-Prevention Training:

- Create a proof of concept for **scenario-based training** in flight simulators dedicated to Vortex Ring State (VRS) training
- Develop a framework to evaluate pilots' performance in VRS recoveries to enhance the simulator flight training experience of both pilots and instructors

Overview of previous work: Scenario-Based Training

Conclusions of Last Year's Work

- **Created and tested a proof of concept for scenario-based training in flight simulator dedicated to VRS-related accident prevention**
- **VRS Recovery Techniques:**
  - Traditional Recovery:
    - **Intuitive reaction** of the pilots during the recovery **contradicted** description of the **technique**
  - Vuichard Recovery:
    - Half of the pilots had training in the recovery but only two attempted to use it and performed it incorrectly
    - **Lack of proficiency** and **training** made it unusable

Virtual Reality Simulator Limitation

- Instructor **not physically** next to the student **in the cockpit**
  - → cannot directly monitor the student's actions on the controls → **May not identify incorrect** recovery **technique**
  - → **Need method to provide instructors and students quantitative feedback on performance**

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Overview of Experiment

Objective: Develop a framework to **evaluate pilots' performance in VRS recoveries** to enhance the simulator flight training experience of both pilots and instructors.

Recovery Aspects:

Correct Application

Develop a set of criteria to determine whether the recovery is performed as defined

Effectiveness

Develop a metric independent of the starting airspeed, vertical speed, and weight

Consistency

Determine the rate of correct application and the spread in efficiency

H125 VR Flight Simulator

Recoveries — **624 Recoveries Recorded**

- **217 Traditional** Recoveries
- **220 Power-Assisted** Recoveries
- **187 Vuichard** Recoveries (incl. 15 from Capt. Vuichard)

Pilots

- **11 Pilots: All** trained in the **Traditional** Recovery, **Half** trained in the **Vuichard** Recovery, **None** trained in the **Power-Assisted** Recovery

Power-Assisted Recovery : Correct Application-Distributions

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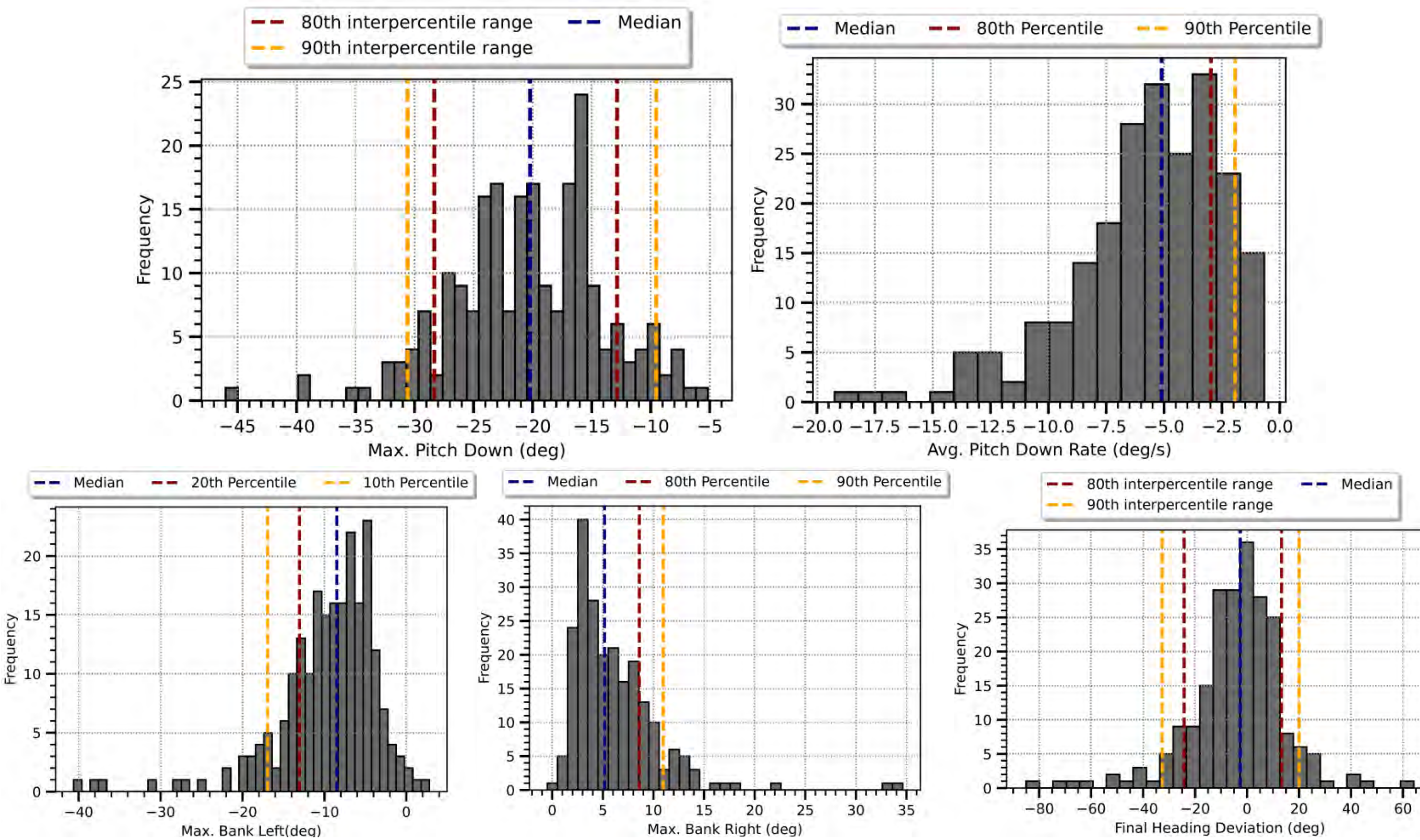
- Introduction
- Experimental Design
- Results: H125 Sim.
- Results: R22 Sim. – R66 Helo.
- Conclusions



Power-Assisted Recovery : Correct Application

Correct Application Criteria:

Collective Input

- If Initial Torque < 90%: **(Normal Initial Torque Situation)**
  - **No overtorque** (Maximum torque <=100%)
  - **Maintain/Increase torque during the recovery** (Maximum torque>= Initial Torque)
  - **Maintain/Increase torque at the beginning of the recovery** (between the start of the recovery and the maximum torque time, the torque does not go below the initial torque - 5 % pts)
- Else: **(High Initial Torque Situation)**
  - **Avoid excessive overtorque** (Maximum torque<= Initial torque + 15 % pts)

Longitudinal Cyclic Input

- **Decisive downward Pitch motion:**
  - Maximum pitch down between 10 and 35 degrees
  - Average absolute pitch down rate to max pitch down faster than 2 deg/sec

Lateral Cyclic and Pedal Inputs

- **Maintain directional control:**
  - Bank -20 to 20 deg
  - Heading deviation smaller than 30 deg

Power-Assisted Recovery: Correct Application - Dataset

- Introduction
- Experimental Design
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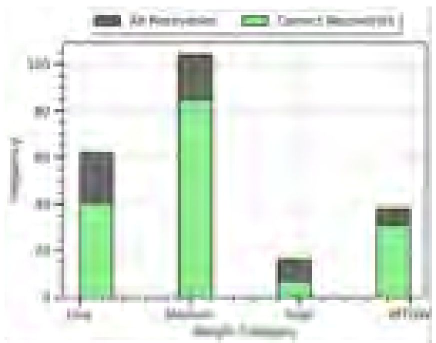

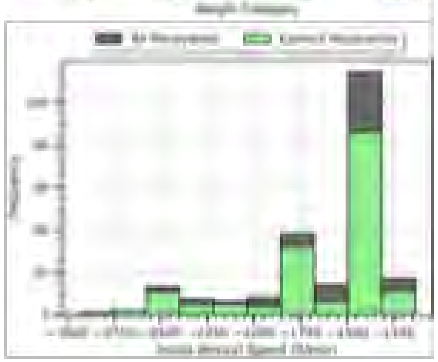

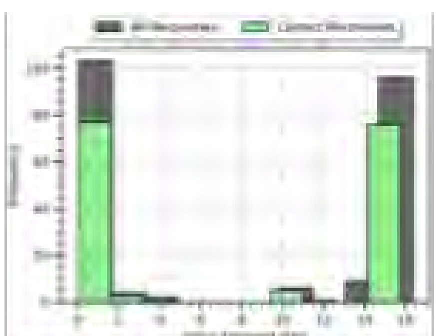

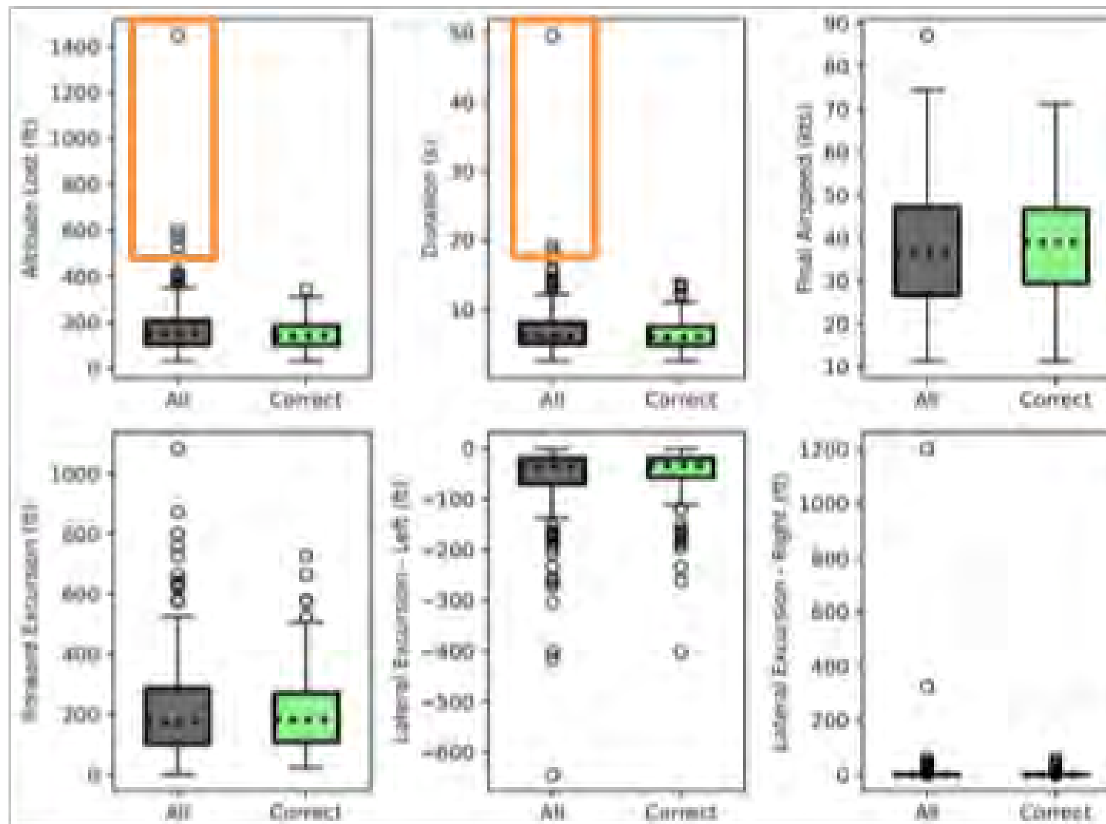

Power-Assisted Recovery : Correct Application

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Pilot	Nb Recs	Nb Correct	% Correct	% Correct Collective	% Overtorque	% Correct Collective motion	% Correct Longcyc	% Correct Pitch	% Correct Pitch Rate	% Low Pitch down	% Correct Latcyc	% Correct Pedals
PilotB	4	1	25	100	0	100	25	100	25	0	100	100
PilotC	32	26	81	96	3	100	84	90	93	9	100	100
PilotD	12	5	41	83	16	91	58	75	58	25	91	83
PilotE	14	6	42	92	7	100	92	100	92	0	100	50
PilotF	7	0	0	85	14	100	0	100	0	0	100	71
PilotG	12	11	91	100	0	100	91	91	91	8	100	100
PilotH	12	6	50	66	33	100	75	91	83	8	91	91
PilotJ	91	82	90	97	0	97	94	94	98	3	93	96
PilotK	7	5	71	85	14	100	85	85	100	14	100	100
PilotO	11	4	36	54	45	90	72	81	90	9	81	63
PilotV	18	17	94	100	0	100	94	94	100	0	100	100
all	220	163	74	92	6	98	84	92	89	5	95	91

Observations

- Same average % overtorque between Power-Assisted and Traditional recovery (6%) -> independent of collective motion
- Only 4 pilots performed correctly over 75% of the time (the same 4 as for the traditional recovery)

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Power-Assisted Recovery
Multi-linear Regression Model – Altitude Lost

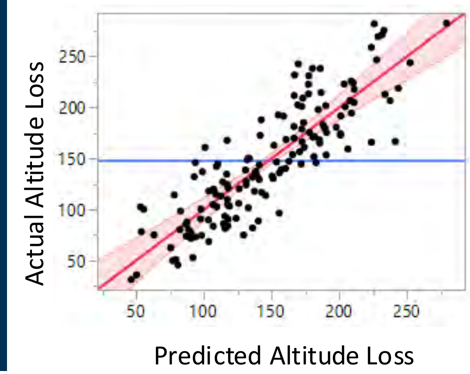
Effectiveness Metric

- Based on altitude loss
- Altitude loss depends on the recovery's initial conditions -> Need to non-dimensional -> Requires estimating the impact of the initial conditions on the altitude loss

Summary of Fit

	0.74
Adjusted R^2	0.72
RMSE	29.7
Mean of Response	148 ft
Observations	149

Actual by Predicted Plot



Parameter	Effect	Impact of Parameter on Altitude Lost during the Recovery
Weight	↗	**Increasing weight increases altitude lost**
Initial Forward Speed	↘	**Increasing speed decreases recovery altitude lost**
Initial Descent Rate	→	Increasing descent rate increases altitude lost **No effect**
Collective Input	↘	**Increasing maximum collective input decreases altitude lost**
Longitudinal Cyclic	↗	There is a downward pitch value that minimizes the altitude lost **Increase the maximum downward pitch increases the altitude lost**
Longitudinal Cyclic rate	↘	**Increasing the average pitch rate to reach maximum pitch down decreases the altitude lost**

Power-Assisted Recovery : Effectiveness & Consistency

Introduction
Experimental Design
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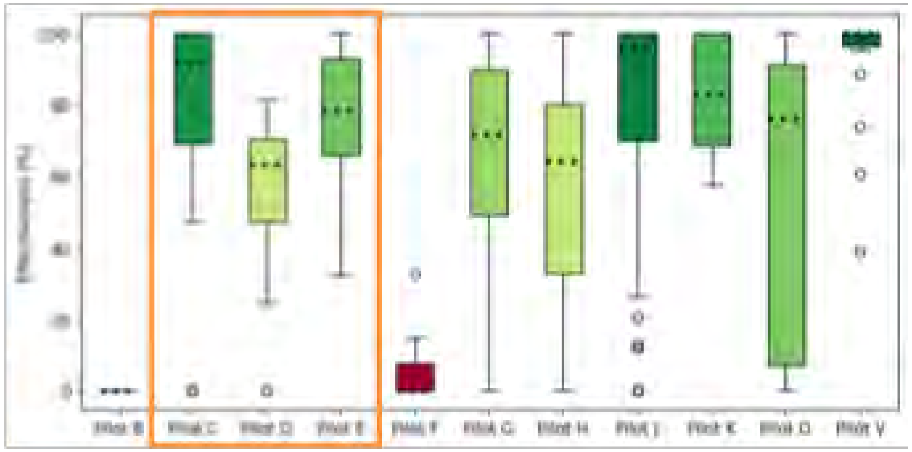

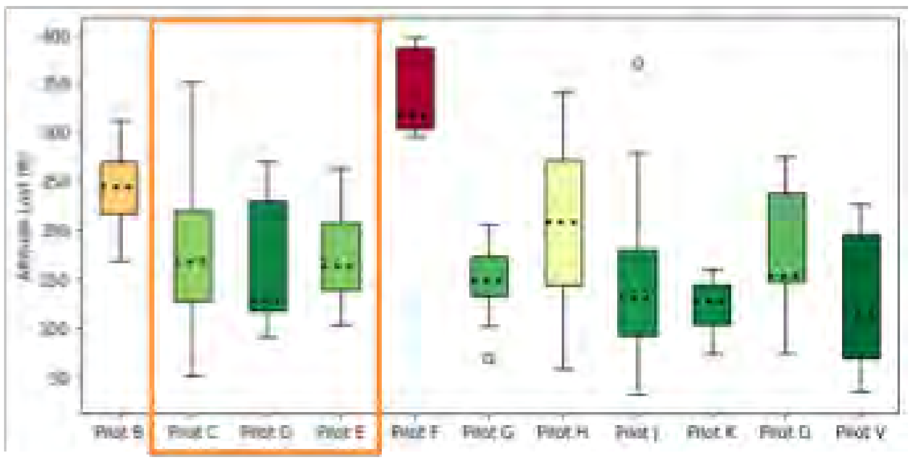

Effectiveness Metric

- Nominal altitude loss: predicted altitude loss at the given starting condition with the most favorable control inputs
- 100%: Recover with less (or equal) than the nominal altitude loss
- 0%: Recover with more than thrice the nominal altitude loss

Observations

- Average altitude loss for pilot D is lower than that of pilots C and E, however effectiveness of pilot D is also lower on average
- Untransformed altitude loss is not a fair measurement of effectiveness

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Power Assisted Recovery: Consistency

- Introduction
- Experimental Design
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Pilot	Nb Recs	Nb Correct	% Correct	Med. Effectiveness (%)	IQR	Range	Med. Effectiveness (%) – Correct only	IQR – Correct only	Range – Correct only
PilotB	4	1	25	0	0	0	0	0	0
PilotC	32	26	81	92	31	100	92	30	100
PilotD	12	5	41	63	23	81	69	11	26
PilotE	14	6	42	78	27	68	69	18	60
PilotF	7	0	0	0	8	33			
PilotG	12	11	91	72	40	100	73	44	100
PilotH	12	6	50	64	47	100	71	29	84
PilotJ	91	82	90	95	30	100	95	30	100
PilotK	7	5	71	83	32	43	83	24	43
PilotO	11	4	36	76	84	100	58	50	91
PilotV	18	17	94	100	4	61	100	1	40
all	220	163	74						

Observations

- Very high correlation between the percentage of correct recoveries for a pilot and the median effectiveness score, unlike the traditional recoveries
- No correlation between the range of effectiveness scores and the number of recoveries flown by the pilots

Summary: Pilot Performance Evaluation Results

H125 Flight Simulator

Correctness

Most common issue observed for each technique:

- **Power-Assisted Technique: Longitudinal** cyclic input (not pitching down fast enough)
- **Traditional Technique: Collective** input (not lowering the collective enough)
- **Vuichard Technique: Lateral** cyclic input (not banking fast enough)

Effectiveness

- **All techniques:** Altitude loss does not fairly represent the effectiveness of the technique, **non-dimensional effectiveness score** takes into account the initial conditions to provide a means of comparison between recoveries

Consistency

- **Power-Assisted Technique: very strong correlation** between the percentage of correct recoveries and the median effectiveness score
- **All techniques: no correlation** between range of effectiveness scores and the number of recoveries flown by a pilot

R22 Flight Simulator vs R66 Helicopter

Observations based on a single pilot → Results must not be generalized

Correctness

- Applied the **correctness criteria** defined in the previous experiment to a single pilot flying in the **R22 simulator and R66 helicopter**
- There was a **very strong correlation** between the pilot's correctness scores in the simulator and helicopter for all techniques

Effectiveness

- Could not develop a non-dimensional effectiveness score for the R66 due to the low number of data points
- Overall, there is a **good correlation** between **altitude loss** in the helicopter and simulator

Consistency

- Overall the **recoveries** were **more consistent in the helicopter than in the simulator,** most likely due to the lower rate of descent in the helicopter and pilot familiarity with the machine

STUDY OF DYNAMIC ROLLOVER

Dynamic Rollover – Definition

Helicopter Flying Handbook:
Dynamic rollovers begin when the ***helicopter starts to pivot laterally*** around its skid or wheel.

For dynamic rollover to occur, three factors must be present:

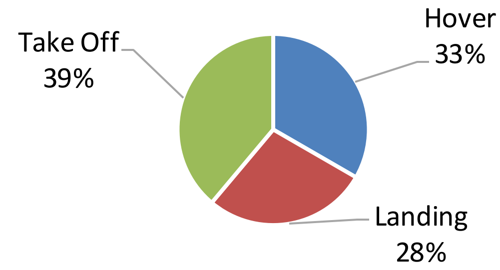
1. *A rolling moment*
2. *A pivot point other than the normal CG of the helicopter*
3. *Thrust > weight*

128 dynamic rollovers in the U.S. since 2008 (NTSB data):

100%
resulted in substantial damage to the aircraft[1]

50%
resulted in some injuries[1]

11%
resulted in serious injuries[1]



Phase of flight of dynamic rollover occurrences for 2022/2023

Previous work:

- Former student's work provides a method to **augment existing Helicopter Flight Data Monitoring (HFDM) systems** using physics-based models
- In addition to measured variables, **additional metrics are derived** for event analysis
- A metric of interest is derived as ***first hitting time*** for dynamic rollovers, to detect potential hazards

Goal: Extend approach by analyzing a wider range of initial conditions and introducing stochastic modeling to derive a risk-based metric for rollover prediction

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Experiments

Table 1: Variable ranges used to create the DOE for the "in-flight" scenario.

Parameter	Min Value	Max Value
Initial height h (ft)	5	50
Roll rate p (deg/s)	-45	45
Pitch rate q (deg/s)	-45	45
Yaw rate r (deg/s)	-45	45
Forward velocity V_x (kt)	-35	35
Lateral velocity V_y (kt)	-35	35
Vertical velocity V_z (ft/min)	-500	500
Wind azimuth $Wind_{az}$ (deg)	0	360
Wind magnitude $Wind_h$ (kt)	0	25
Ground slope (deg)	0	25
Slope orientation ϕ (deg)	0	360
Lateral cyclic X_a (%)	-30	30
Longitudinal cyclic X_b (%)	-30	30
Collective input X_c (%)	-30	30
Pedals input X_p (%)	-30	30

- Dynamic simulations of the **uncontrolled helicopter** were run using the FlightLab simulation software
- In each case, the helicopter started from an **in-flight, near-ground state**, representing **hover, hover taxi, and landing scenarios** (61% of accidents)
- A design of experiments was created to derive **optimal combinations of initial parameters**
- 28,000 simulations were run, and the ***first hitting time*** was recorded for each set of parameters

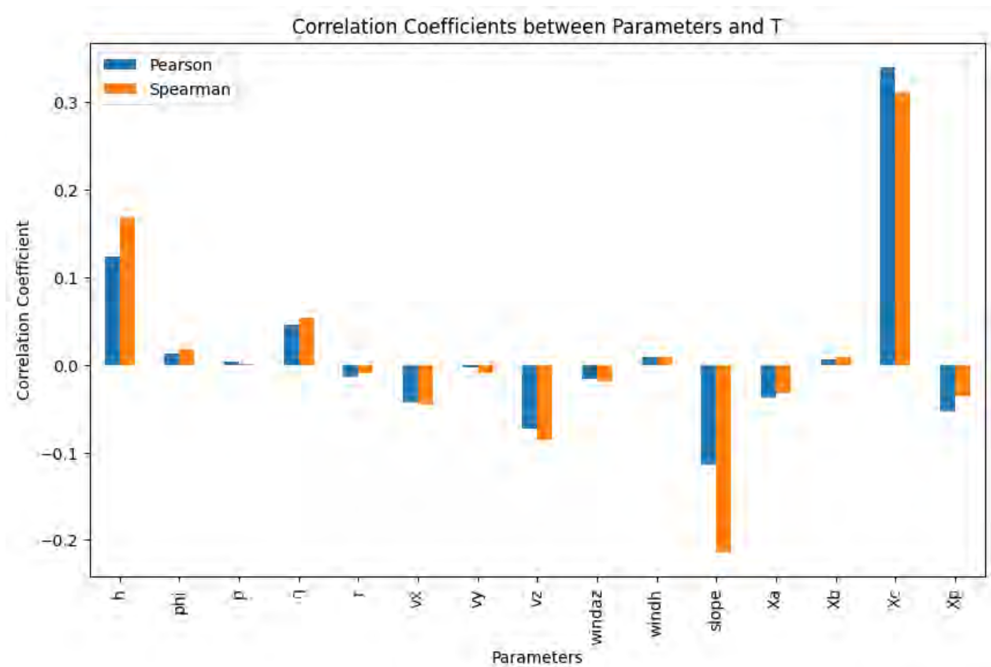
Identifying Significant Parameters

Correlation Coefficients:

- Correlation coefficients between the **first hitting time** and **each parameter** were calculated

- The sign of the coefficients indicate the **direction of the relationship**, while the absolute value (0 to 1) represent the **strength of the relationship**

- **Variables most correlated** with the first-hitting-time are the **slope, height, lateral speed, lateral cyclic, and collective input**



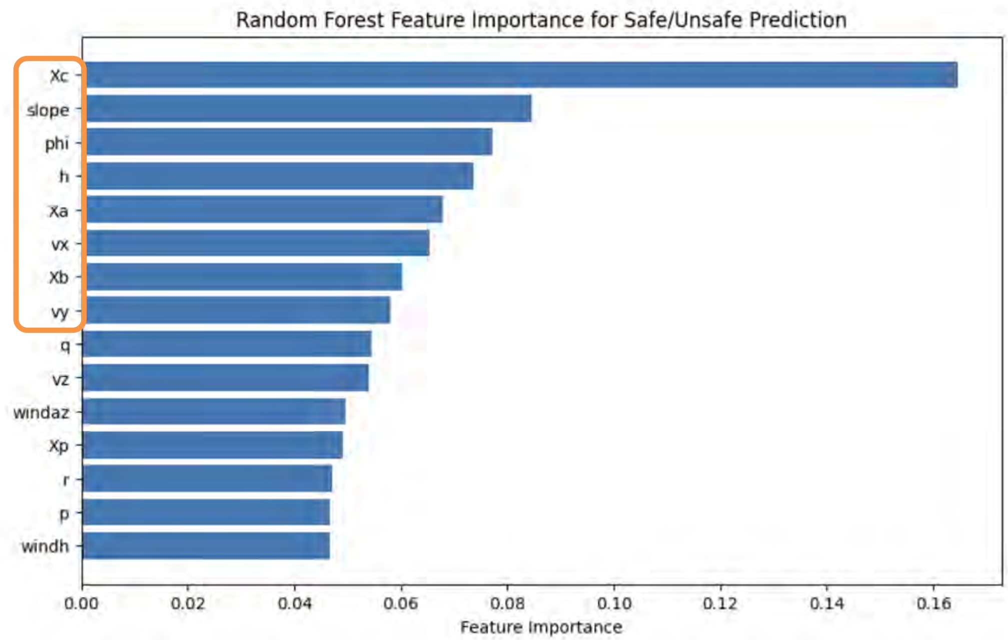
Pearson coefficients: measure linear relationship

Spearman coefficients: measure monotonic relationship

Identifying Significant Parameters

Feature Importance:

- A **Random Forest classification** model was created to **predict safe/unsafe cases**[1], based on a predefined threshold (2.5s)
- The **Feature Importance** measures the weight of each variable to the choice of the output (safe or unsafe)
- Most **important parameters** include the **collective input, slope parameters, initial height, cyclic inputs, and horizontal speed** (about 65% of total variability)



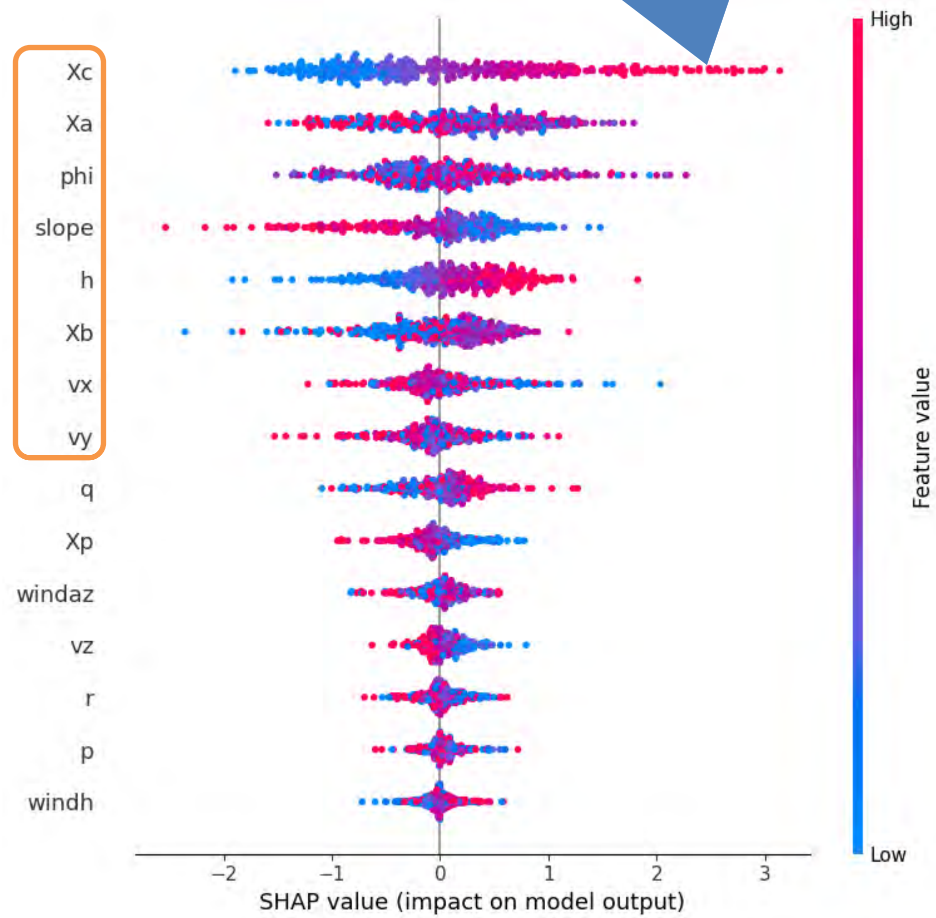
[1] Here, safe/unsafe only means above/under the first-hitting-time threshold. It is not an actual, comprehensive measure of the safety of a situation.

Identifying Significant Parameters

High Xc (red) significantly increase T

Shap Values:

- Measures whether a **variable pushes up** (shap>0) or **down** (shap<0) the output value (**first hitting time**)
- More **spread** means more **variability** induced by different values of the variable
- Main parameters: slope, Xc, Xa, h, vy

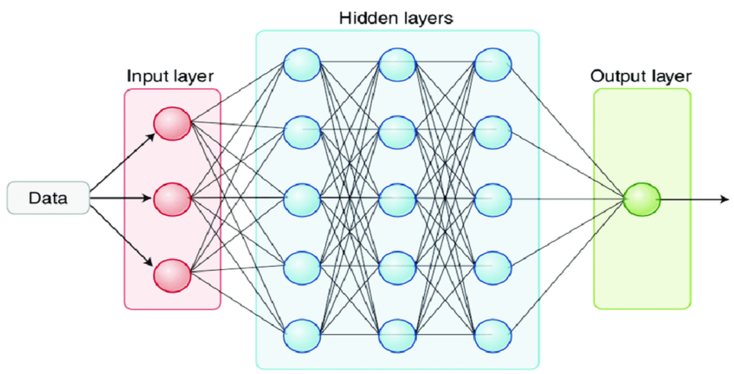


T: first-hitting-time
Phi: slope orientation relative to helicopter

Probabilistic Modeling

Selected Parameters

- Slope magnitude and orientation
- Collective input Xc
- Lateral cyclic Xa
- Longitudinal cyclic Xb
- Height h
- Horizontal speed Vx,Vy



Probabilistic Neural Network

Log-normal distribution

Distribution of potential values for first hitting time (T) is induced by unknown parameters

A ***probabilistic model*** of the first-hitting-time was trained to predict the output distribution, enabling the ***identification of boundaries*** that are ***robust*** to variations in other variables.

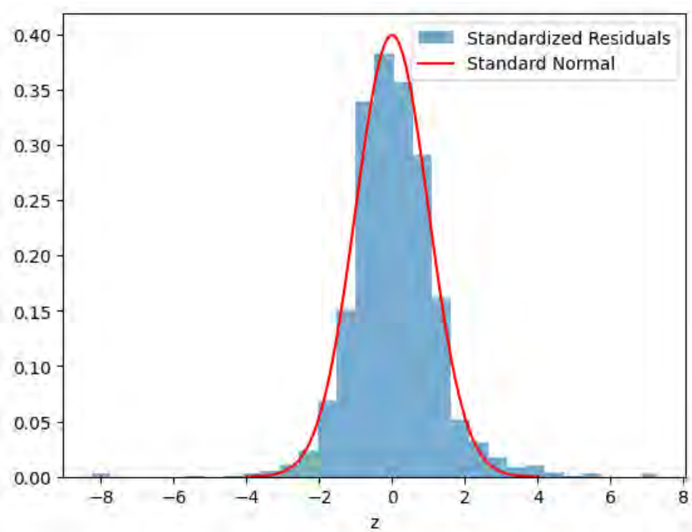
Training the Model

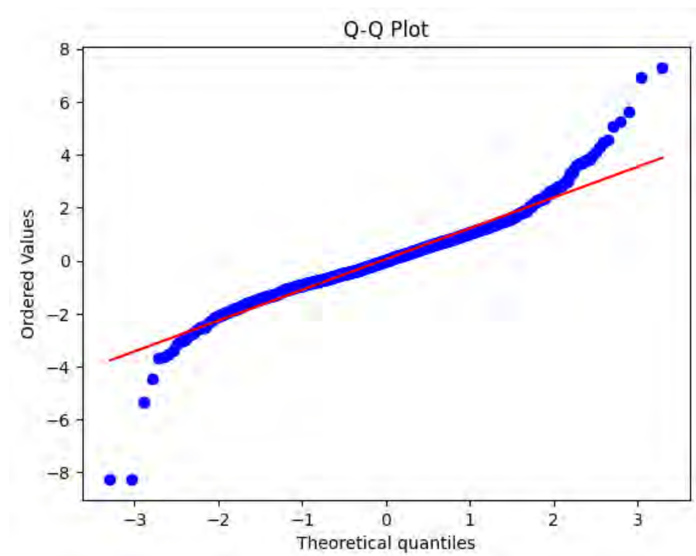
- The probabilistic model was trained using **Maximum Likelihood Estimation**, with right censoring due to the limited duration of simulations (10 s):

$$\max_{\theta}\left(\mathbb{E}_{(x_i,T_i)\text{ uncensored}}\left[\log p\left(T_i \mid \mu_\theta(x_i),\sigma_\theta(x_i)\right)\right]+\mathbb{E}_{(x_i,T_i)\text{ censored}}\left[\log p\left(T \geq 10\text{ s} \mid \mu_\theta(x_i),\sigma_\theta(x_i)\right)\right]\right). \quad (3)$$

T is first hitting time

- The **goodness of fit** was assessed using the standardized residuals for the predicted distribution of $\log T$, which should follow a standard normal distribution

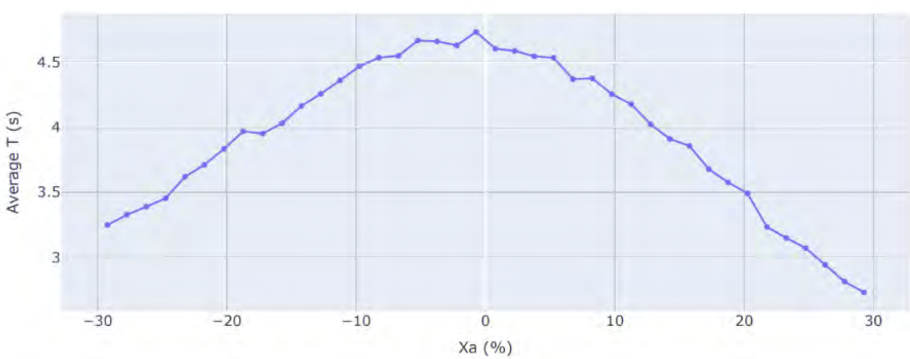




Influence of Parameters

Monte Carlo simulations with the model mean enable the analysis of trends:

- **Monotonic increase** of **first hitting time with** the **initial height**
- Relatively **low impact** of the **ground slope under 8 deg**, then linear decrease of first-hitting-time
- **Parabolic influence** of both **lateral** and **longitudinal cyclic** inputs on first hitting time, peaking near trimmed values
- **Collective input** has the **strongest impact** on first hitting time



Example: Evolution of average first hitting time w.r.t. lateral cyclic input

- **Ground slope parameters** (angle and orientation) **interact** with other variables, altering the ranges resulting in high/low values of the first hitting time

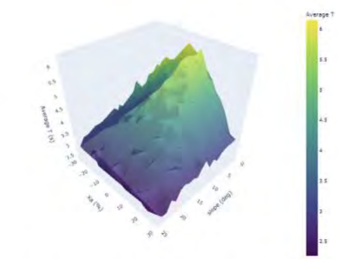


Figure 10: Average first hitting time for different slope angles and lateral cyclic inputs X_a.

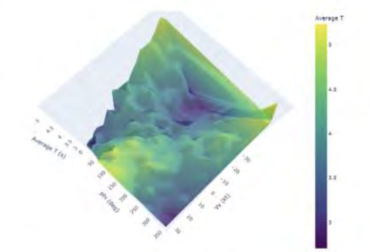


Figure 12: Average first hitting time for different slope orientations ϕ and lateral velocities V_y.

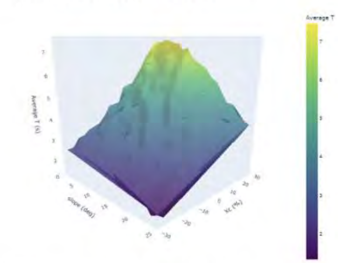


Figure 11: Average first hitting time for different slope angles and collective inputs X_c.

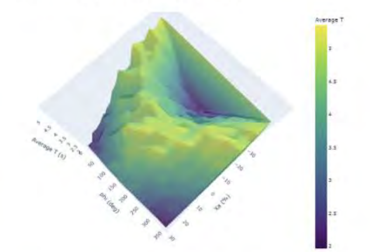
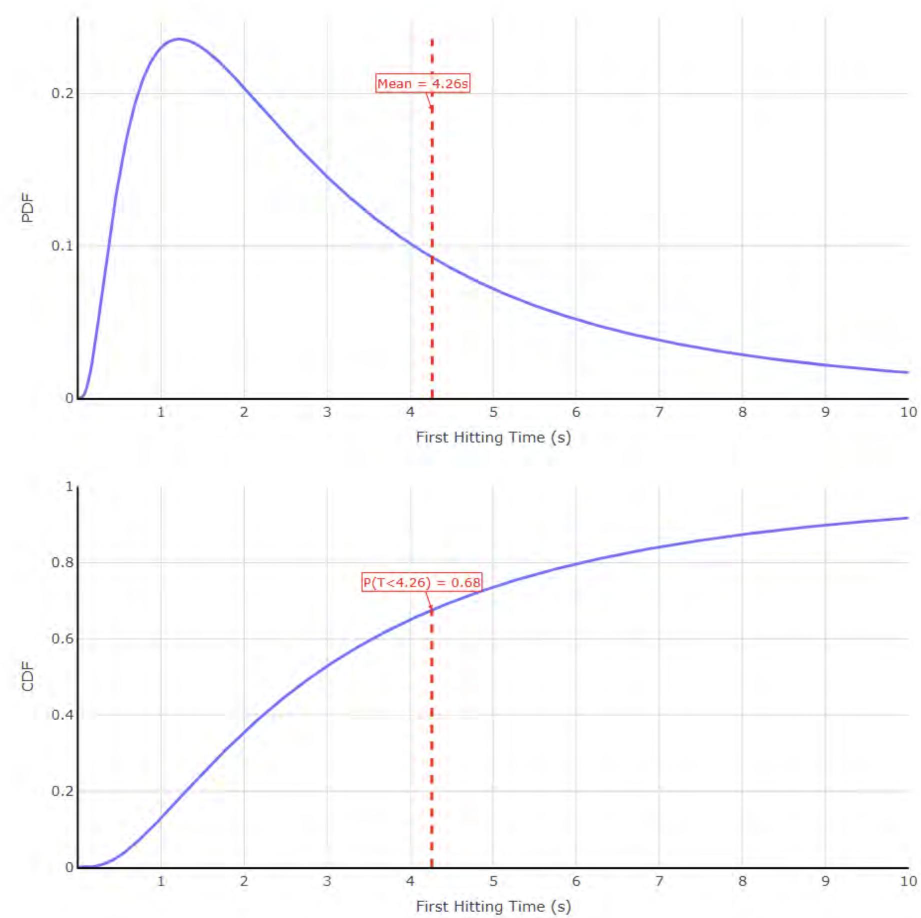


Figure 13: Average first hitting time for different slope orientations ϕ and lateral cyclic inputs X_a.

Need for a Probabilistic Metric

The previous analysis only considered the ***average first hitting time*** for a set of conditions. Is this enough?

The predicted distribution shows ***a high risk of low first hitting time***, despite the average of 4.26s.
This needs to be accounted for when detecting safety events using flight data.



Probabilistic Approach

Approach followed for the definition of a risk-based metric:

Step 1
Choose a "safe" first hitting time threshold T_c

Step 2
Estimate $P(T<T_c)$ in various conditions using the probabilistic model

Step 3
Generate regression model using ANNs

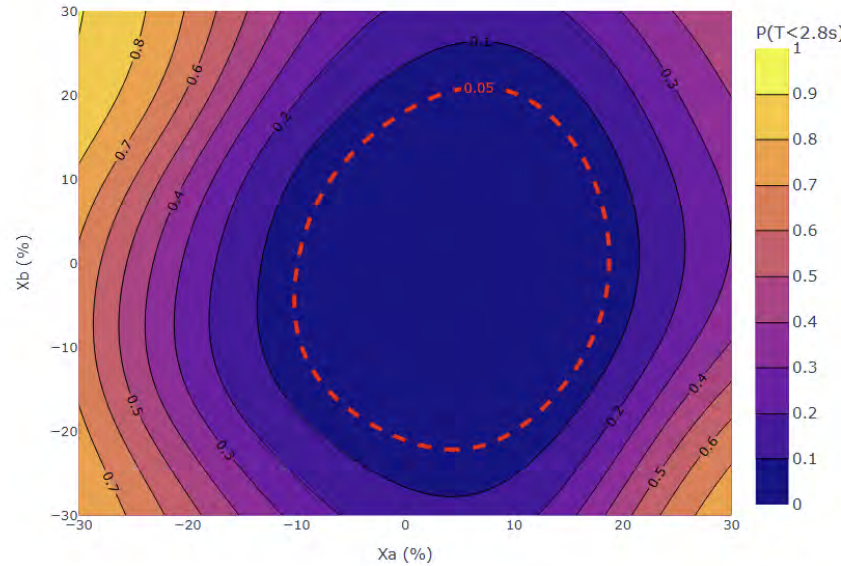
Step 4
Visualize the risk $P(T<T_c)$ using contour plots

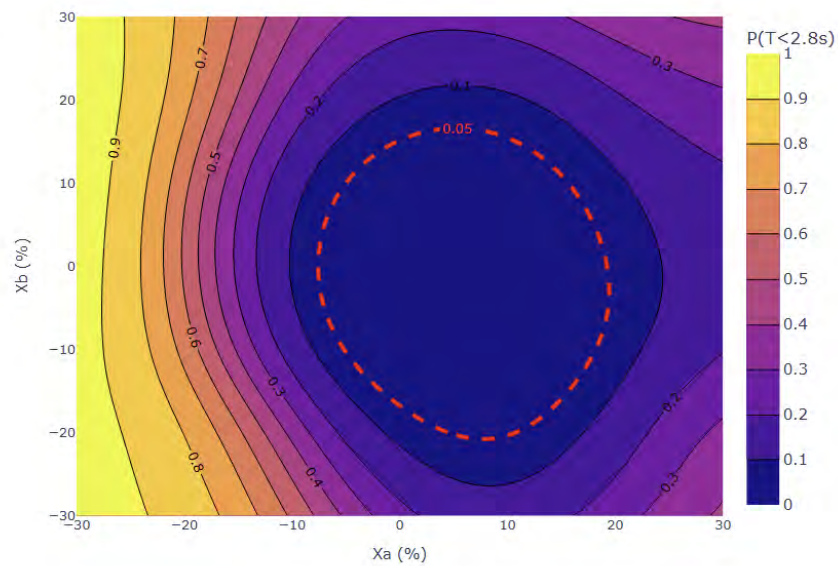
Step 5
Choose a risk threshold to visualize safe conditions

This process was ***automated*** and implemented into a ***visualization environment*** to easily compare various conditions and their associated risk

Visualizing the Risk

The final ***probabilistic metric*** can be visualized using contour plots.
Safe conditions can be visualized after choosing an appropriate risk threshold.





Modifying the conditions changes the contours and the safe areas.
For instance, an ***increased slope*** of 10 degrees **shifts** the **safe cyclic input to the right**.

Conclusion

- Dynamic rollovers remain a major safety concern during low-altitude helicopter operations
- This work focused on identifying **precursors to dynamic rollover events** through high-fidelity simulation and data-driven analysis
- Key influencing factors were identified, including **control inputs, ground slope**, and **initial flight conditions (speed and height)**
- A **probabilistic modeling approach** was developed to predict the distribution of first hitting times, offering a more robust assessment than deterministic metrics
- The proposed **risk-based framework** enables the definition of **safe operating regions**, tailored to operator preferences and visualized through intuitive contour plots
- This method provides a foundation for improving **helicopter operations** and **HFDM**

Dissemination of Project Outcomes – Technical Conferences and Meetings

	HAI HELI-EXPO	PEGASAS	AIAA	Other
2015	Presentation & Posters		AVIATION 2015: 1 Paper & Presentation	41st 2015: 1 Paper & Presentation
2016	Presentation & Posters		SCITECH 2016: 4 Papers & Presentations; AVIATION 2016: 3 Papers & Presentations	72nd Annual Forum and Technology Display May 17-19, 2016: 1 Paper & Presentation
2017	Presentation & Posters		AVIATION 2017: 1 Paper & Presentation	
2018	Presentation & Posters		AVIATION FORUM: 1 Paper & Presentation	

Dissemination of Project Outcomes – Technical Conferences and Meetings

2019	2019 HAI HELI-EXPO 2 Presentations & Posters	PEGASAS	SCITECH FORUM 1 Paper & Presentation	FORUM 75 4 Papers & Presentations Booth & Posters
2020	2020 HAI HELI-EXPO 2 Presentations	PEGASAS	AVIATION FORUM 1 Paper & Presentation	
2021		PEGASAS		FORUM 77 4 Papers & Presentations
2022	2022 HAI HELI-EXPO 1 Presentation	PEGASAS		FORUM 78 1 Paper

Dissemination of Project Outcomes – Technical Conferences and Meetings

2023

1 Paper & Presentation

1 Paper

2024

1 Paper

2025

1 Paper & Presentation

2 Papers