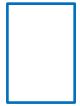


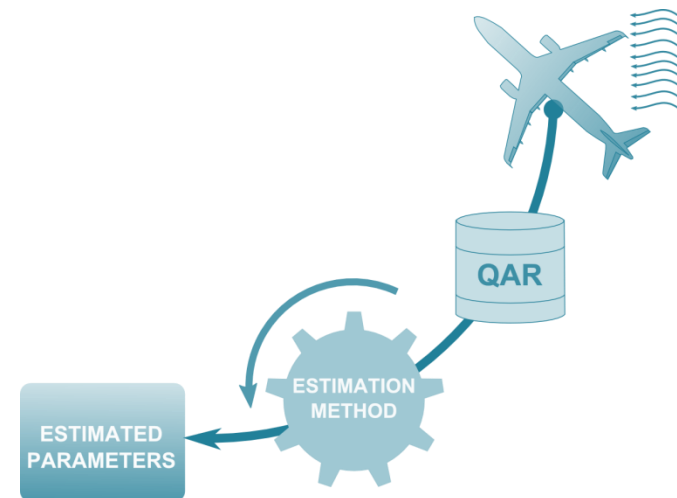
# Extracting Unmeasured Parameters Using Estimation Method

*.... Looking Deeper into the Data*

Javensius Sembiring  
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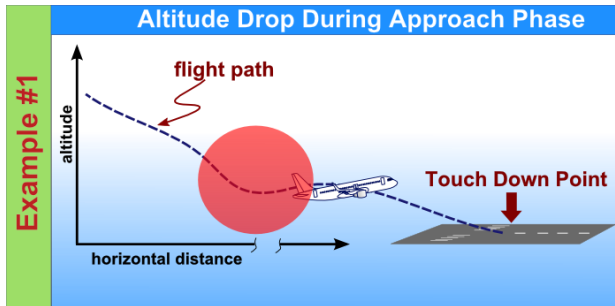
1. Background
2. Technique Used in Flight Vehicle System Identification
3. Case Study
4. Implementation and Results
5. Conclusions



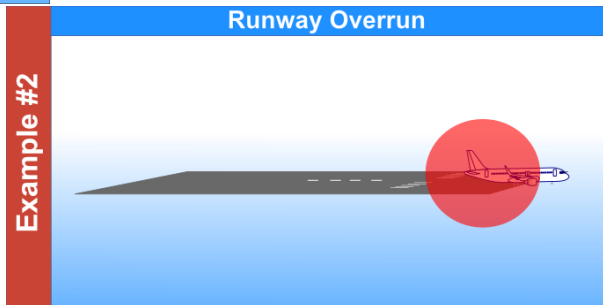
# 1. BACKGROUND

## ▪ FDM State of the Art:

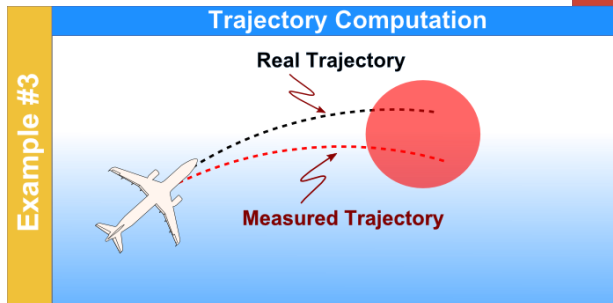
*‘Based on recorded variables and analytical analysis’.*



- Elevator (jammed or not ?)
- Wind speed – *but we only have horizontal wind speed.*
- ?



- Spoiler deployment.
- Thrust Reverser.
- Brakes.
- ?



- Yaw, pitch, roll angles.
- Latitude, longitude, altitude.
- ?

# 1. BACKGROUND

But how if all the measured variables *do not provide us with sufficient information* which enable us to investigate the cause of the event (or the worst case might be an incident/accident)



Image courtesy : [www.npr.org](http://www.npr.org)

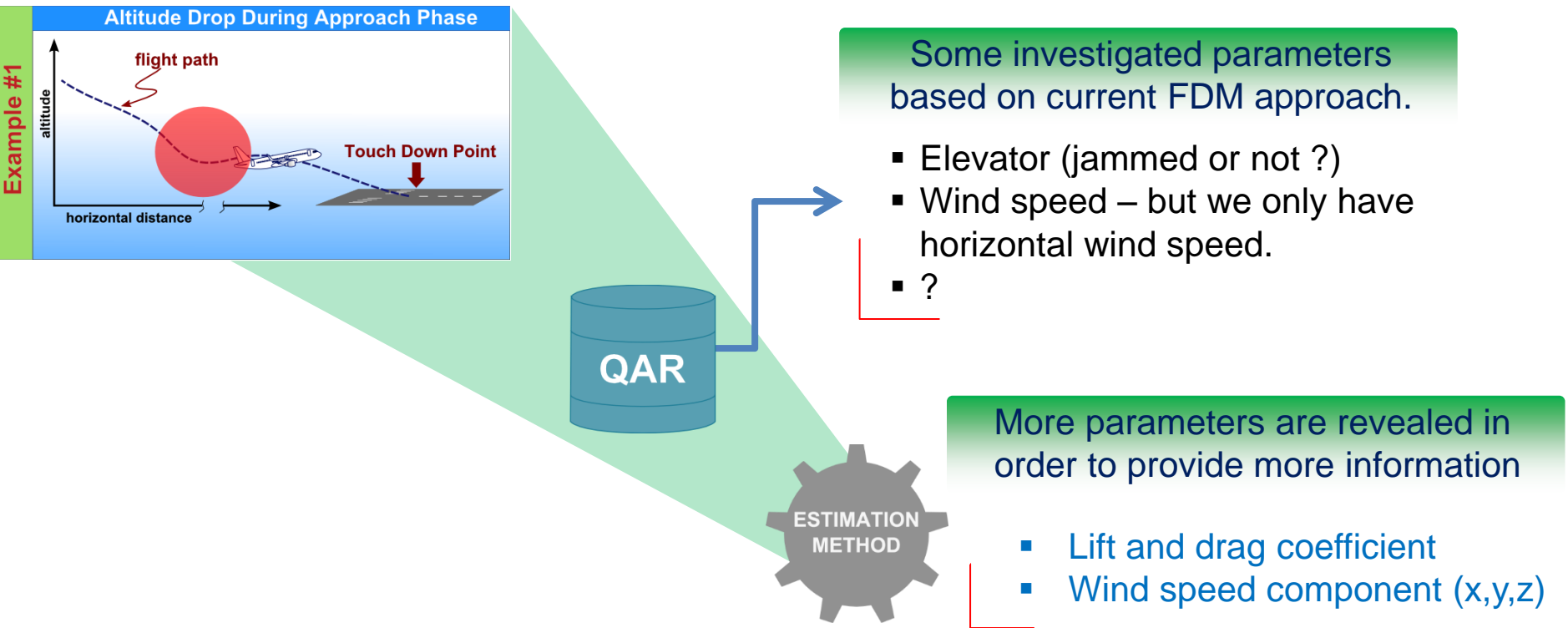
*One answer might be ....*

**We need to look deeper into  
the data!**

# 1. BACKGROUND

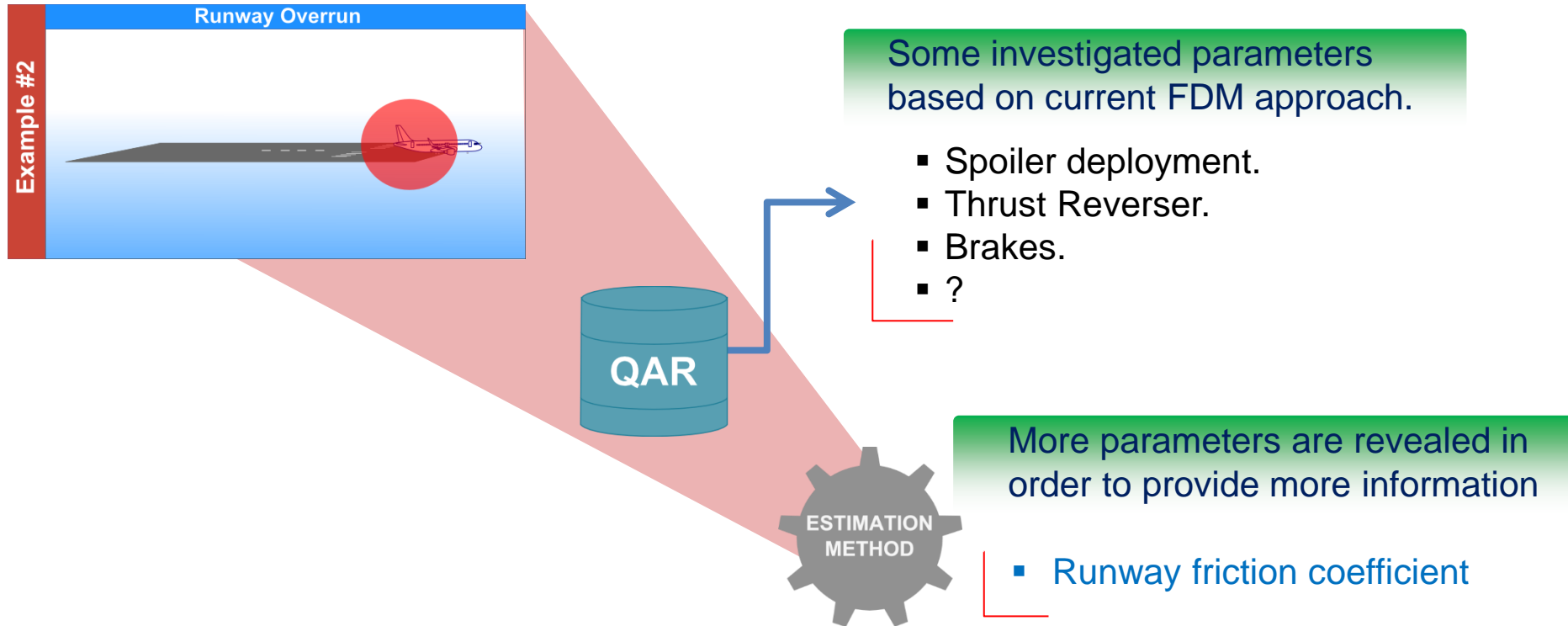
## ■ Beyond FDM State of the Art:

- Extracting parameters which are not measured on QAR data.
- These unmeasured parameters provide information which can be used for event detection or incident/accident investigation.



# 1. BACKGROUND

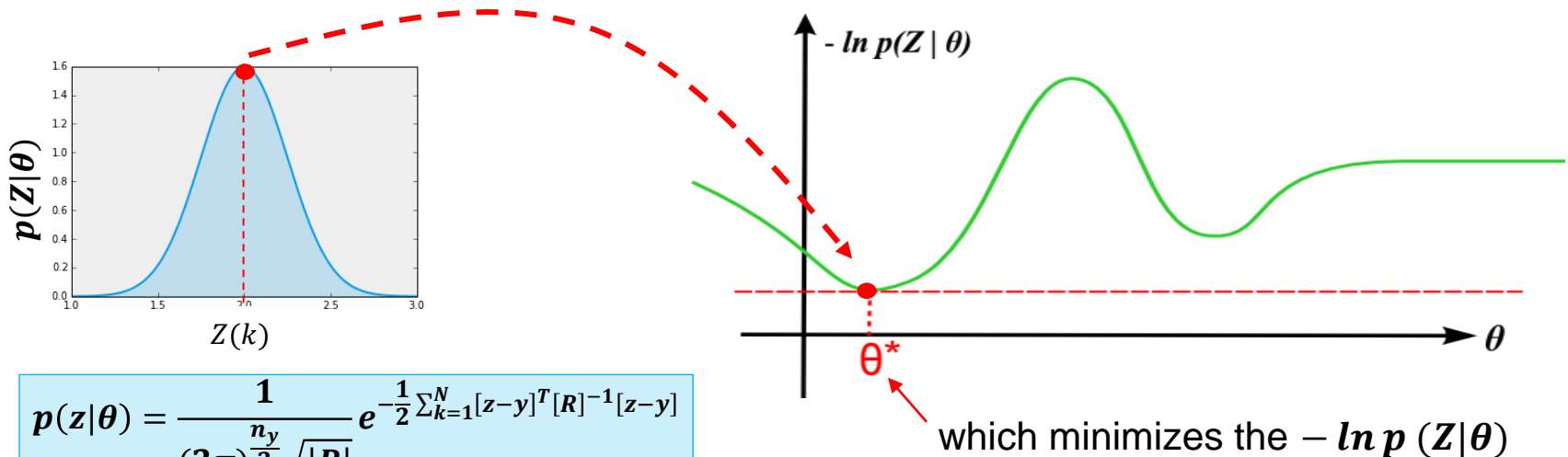
## ▪ Beyond FDM State of the Art



## 2. TECHNIQUE USED in FLIGHT SYSTEM IDENTIFICATION

- The technique called Output Error Method is used for estimating the unmeasured/unrecorded parameters.
- This technique is commonly used in Flight Vehicle System Identification.
- The Output Error Method works based on Maximum Likelihood principle.

*‘ Select parameters  $\theta$  which maximize the conditional probability of measurement ( $Z$ ) given parameters ( $\theta$ ) or which minimizes the  $-\ln(p(Z|\theta))$ ’*



$$p(z|\theta) = \frac{1}{(2\pi)^{\frac{n_y}{2}} \sqrt{|R|}} e^{-\frac{1}{2} \sum_{k=1}^N [z-y]^T [R]^{-1} [z-y]}$$

$Z$  = measurement

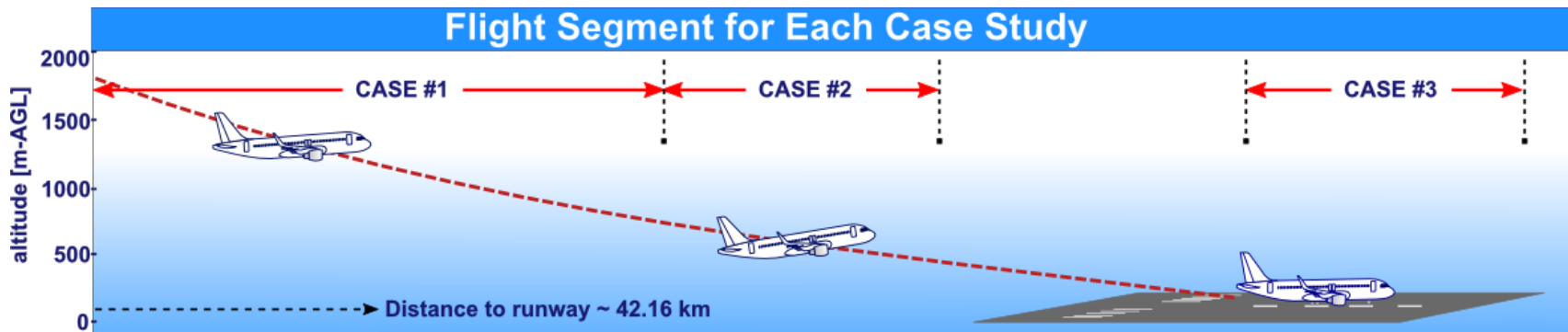
$y$  = model -- function of  $\theta$

$R$  = measurement covariance matrix

# 3. CASE STUDY

## ■ Cases:

- Case #1 → Lift & drag coefficient due to flap deflection.
- Case #2 → Wind speed component estimation.
- Case #3 → Runway friction and aerodynamic coefficient.



## ■ Data used: A340-600 QAR Data. Variables include:

- Measurement from accelerometers ( $a_x, a_y, a_z$ )
- Measurement from gyroscope (yaw, pitch, roll, and their rate).
- Measurement from pitot tube,  $\alpha$  and  $\beta$ - vane (airspeed, AoA, AoS).
- Measurement from altimeter (altitude).

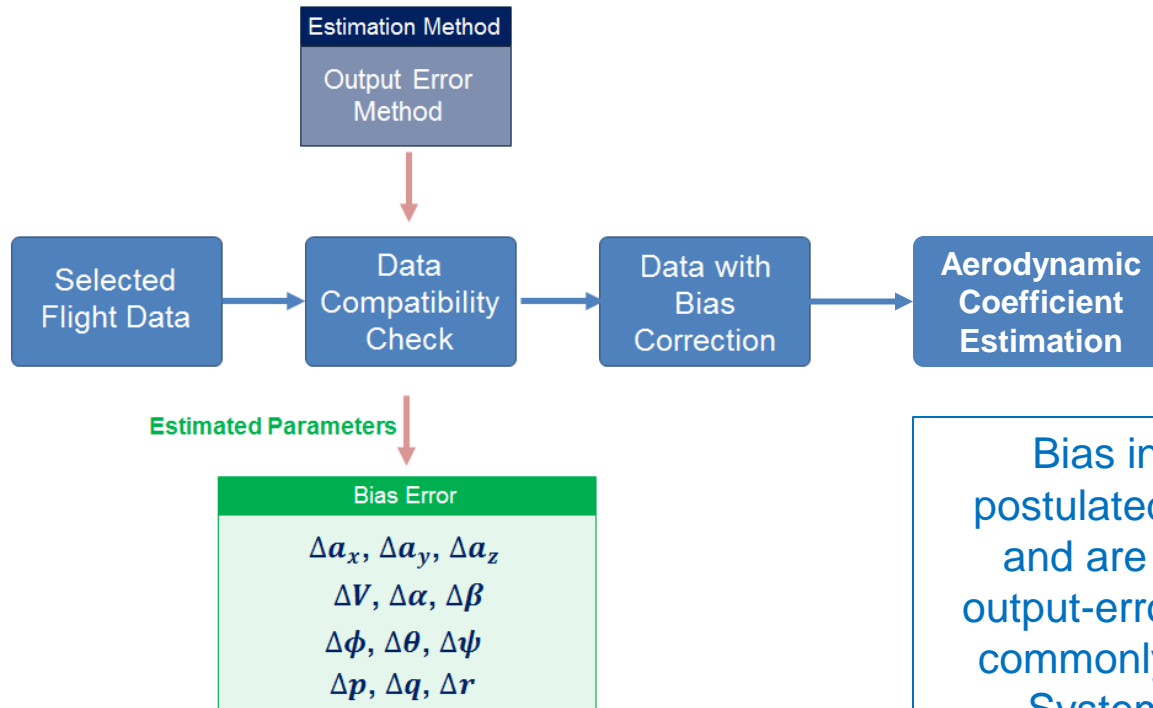
- In every segment, the bias in the measurement is estimated in order to improve the accuracy of the estimates.



### 3. IMPLEMENTATION AND RESULTS

#### ▪ Case #1: Lift & Drag Coefficient Increment due to Flap Deflection

##### Estimation Step Workflow



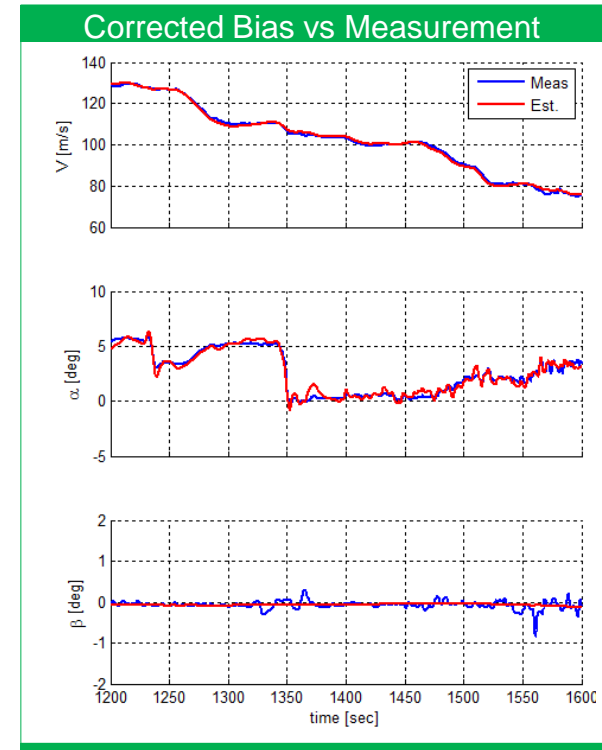
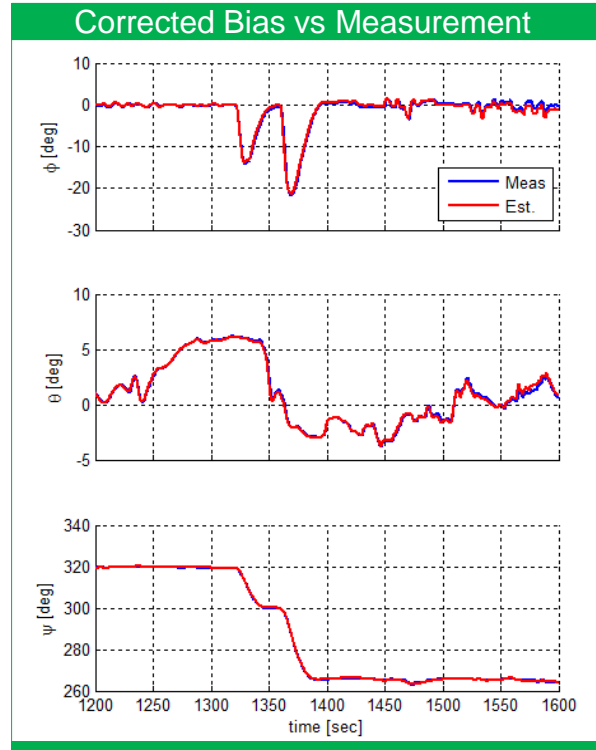
Bias in the measurement are postulated in **kinematic equations** and are estimated by employing output-error method. This process is commonly applied in Flight Vehicle System Identification for **data compatibility check** purpose.

- $\Delta a_{x,y,z}$ : bias in accelerometer sensor.
- $\Delta V, \Delta \alpha, \Delta \beta$ : bias in flow measurement.
- $\Delta \phi, \Delta \theta, \Delta \psi, \Delta p, \Delta q, \Delta r$ : bias in gyroscope sensors.

# 3. IMPLEMENTATION AND RESULTS

## Case #1: Lift & Drag Coefficient Increment due to Flap Deflection

### Bias Estimation Results



Parameters	Value	Std.Dev.
$\Delta a_x$ :	-7.027E-03 [m/s <sup>2</sup> ]	7.085E-04
$\Delta a_y$ :	-2.392E-01 [m/s <sup>2</sup> ]	7.671E-04
$\Delta a_z$ :	2.021E-01 [m/s <sup>2</sup> ]	7.671E-05
$\Delta p$ :	-5.261E-04 [rad/s]	6.268E-07
$\Delta q$ :	2.869E-06 [rad/s]	5.930E-07
$\Delta r$ :	-5.969E-04 [rad/s]	8.718E-07

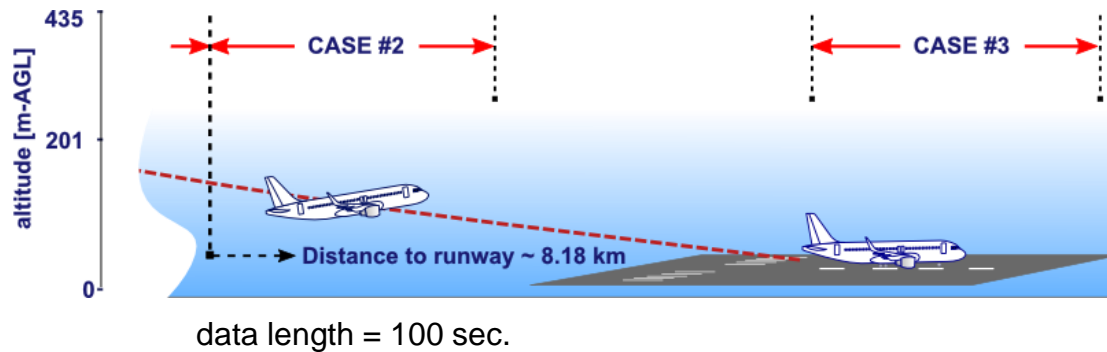
Parameters	Value	Std.Dev.
$\Delta V$ :	1.305E-01 [m/s]	4.572E-02
$\Delta \alpha$ :	-1.527E-02 [rad]	3.243E-04
$\Delta \beta$ :	-1.398E-03 [rad]	3.373E-05
$\Delta \phi$ :	5.236E-03 [rad]	2.184E-04
$\Delta \theta$ :	-1.057E-03 [rad]	8.299E-05
$\Delta \varphi$ :	-1.141E-02 [rad]	2.009E-04

- **Case #1: Lift & Drag Coefficient Increment due to Flap Deflection**

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### 3. IMPLEMENTATION AND RESULTS

#### Case #2: Wind Speed Component Estimation – Postulated Model



$$V_w^E = C_b^E V_b - C_b^E C_a^b V_a$$

$V_a$  = Airspeed in aerodynamic frame.

$V_b$  = Speed in body frame.

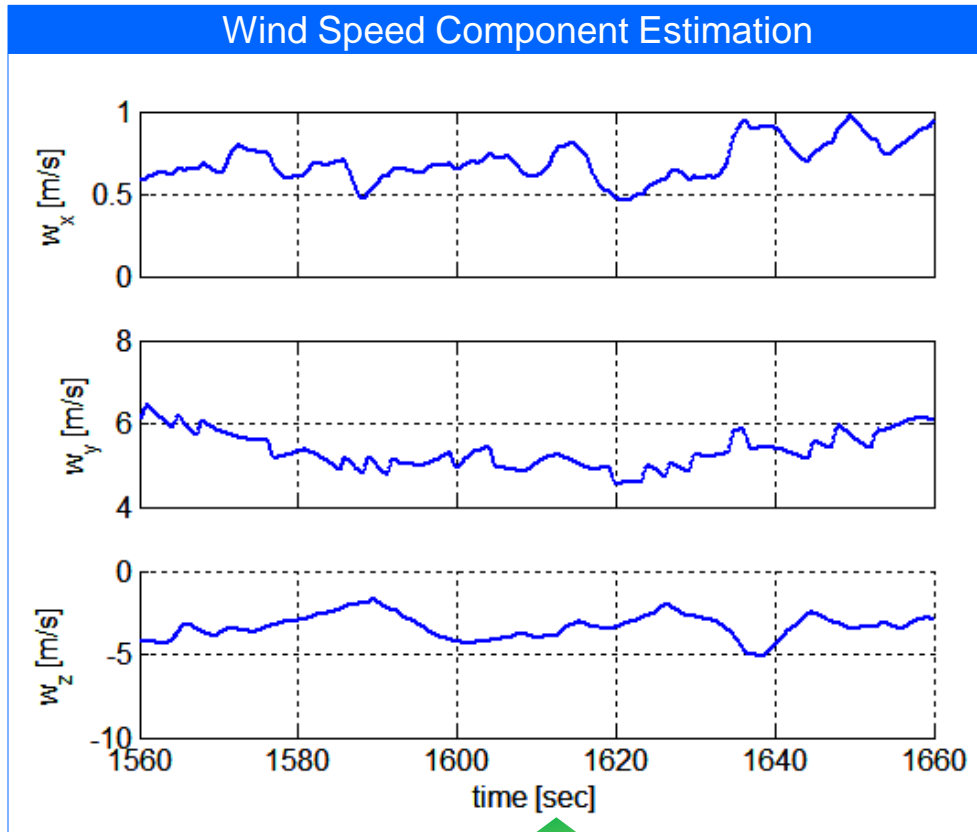
$V_w^E$  = wind speed component earth frame.

$C_b^E$  = matrix transformation from body to earth frame.

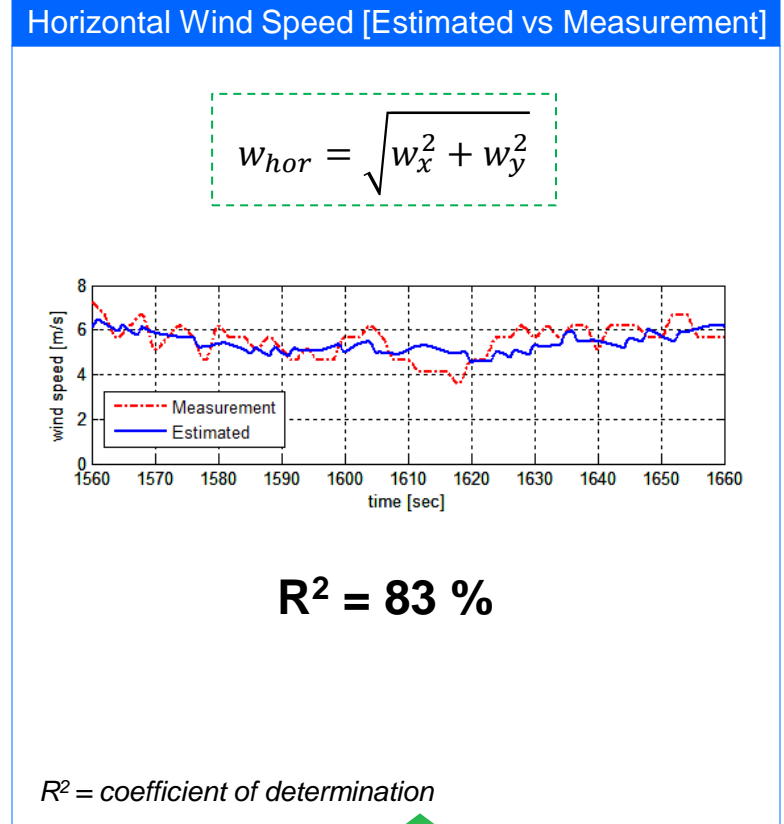
$C_a^b$  = matrix transformation from wind to body frame.

### 3. IMPLEMENTATION AND RESULTS

#### ■ Case #2: Wind Speed Component Estimation (Results)



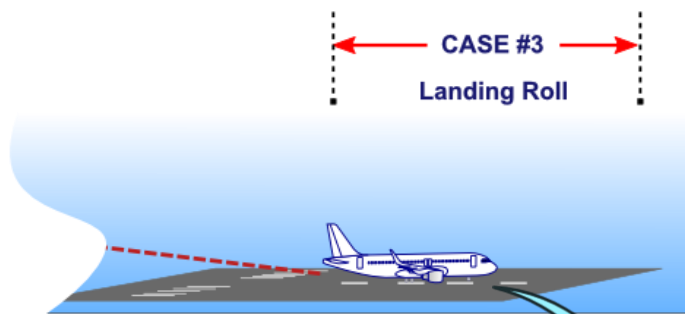
These components are not recorded  
on QAR Data



Proof of concept – comparison between  
measured horizontal wind speed and  
reconstructed horizontal wind speed.

# 3. IMPLEMENTATION AND RESULTS

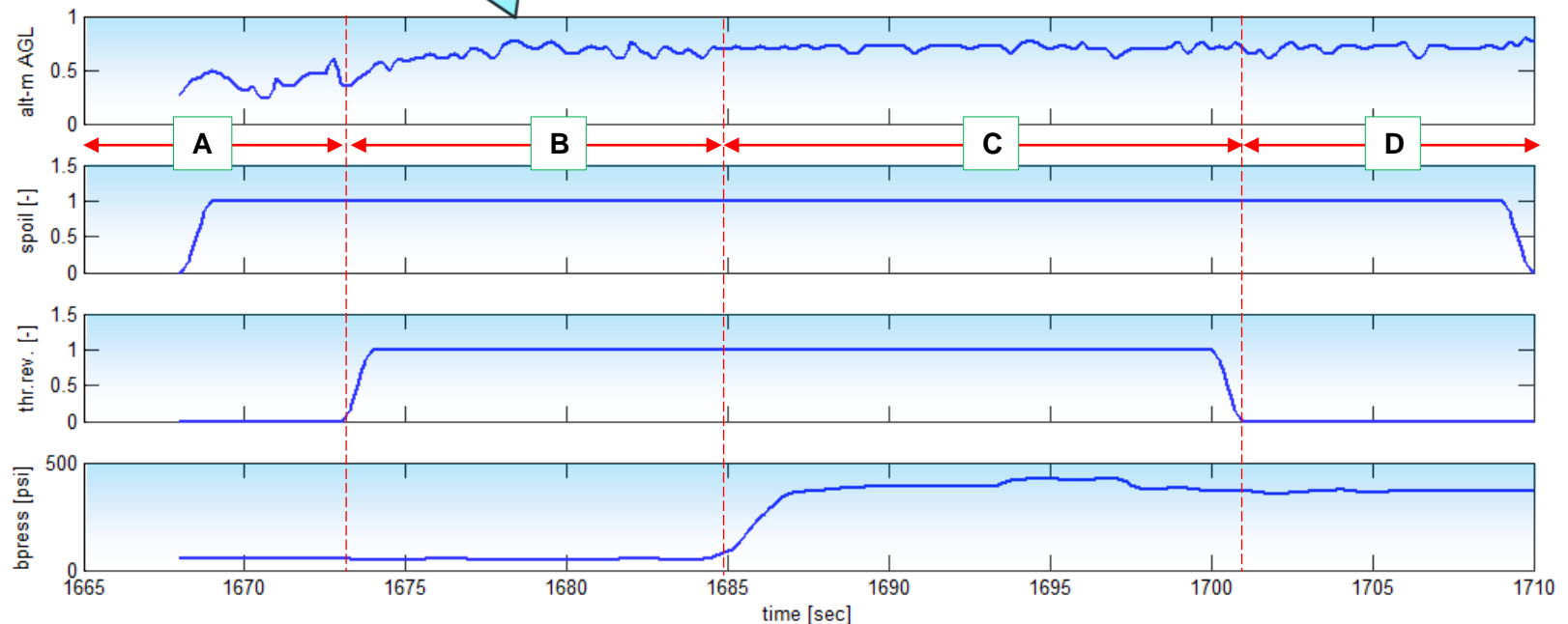
## Case #3: Runway Friction, Lift and Drag Coefficient Estimation (Data Selection)



data length = 45 sec.

### Landing Roll Segmentation

- A: Spoiler Deployed
- B: Spoiler + Thrust Reverser Deployed
- C: Spoiler + Thrust Reverser Deployed + Braking
- D: Spoiler Deployed + Braking



### 3. IMPLEMENTATION AND RESULTS

#### Case #3: Runway Friction, Lift and Drag Coefficient Estimation (Postulated Model)

Phase A: Spoiler Deployed

$$m \cdot \hat{a}_x \approx -\bar{q} \cdot S \cdot C_{D,S} - \mu_{roll} \cdot (m \cdot g - \bar{q} \cdot S \cdot C_{L,G}) + \delta_T T_0$$

Phase B: Spoiler + Thrust Reverser Deployed

$$m \cdot \hat{a}_x \approx -\bar{q} \cdot S \cdot C_{D,S} - \mu_{roll} \cdot (m \cdot g - \bar{q} \cdot S \cdot C_{L,G}) - \delta_T T_{0,REV}$$

Phase C: Spoiler + Thrust Reverser Deployed + Braking

$$m \cdot \hat{a}_x \approx -\bar{q} \cdot S \cdot C_{D,S} - \mu_{rollbrk} \cdot (m \cdot g - \bar{q} \cdot S \cdot C_{L,G}) - \delta_T T_{0,REV}$$

Phase D: Spoiler Deployed + Braking

$$m \cdot \hat{a}_x \approx -\bar{q} \cdot S \cdot C_{D,S} - \mu_{rollbrk} \cdot (m \cdot g - \bar{q} \cdot S \cdot C_{L,G}) - \delta_T T_0$$

Corrected acceleration is obtained from previous step (bias correction) and each equation is then solved by using least square method

$$param = [C_{D,S}, \mu_{roll}, \mu_{rollbrk}, C_{L,G}, T_0]$$

← Parameters to be estimated.

$\hat{a}_x$  : corrected horizontal acceleration

$m$  : mass

$\bar{q}$  : dynamic pressure

$g$  : gravity constant

$C_{D,S}$  : drag coef. during spoiler deployed.

$\delta_T$  : throttle input

$S$  : wing area

$\mu_{roll}$  : rolling friction coef.

$\mu_{rollbrk}$  : rolling+braking friction coef.

$C_{L,G}$  : lift coef. during ground run.

$T_0$  : thrust

- **Case #3: Runway Friction, Lift and Drag Coefficient Estimation** (Results)

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## 5. CONCLUSIONS

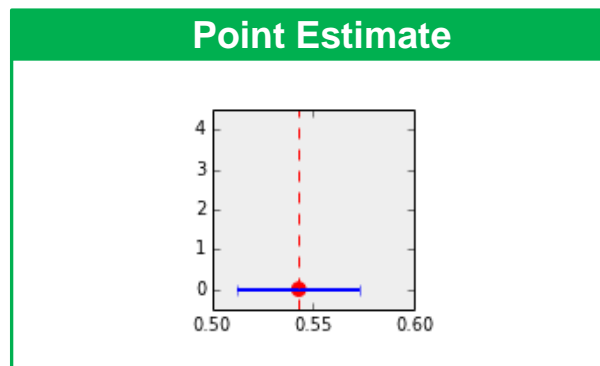
- Estimation technique, commonly applied in System Identification field, can also be implemented on QAR data to estimate the unmeasured/unrecorded parameters.
- The extracted parameters can be used for event detection or for investigating the cause of incident/accident in which the measured variables on QAR data are not able to provide such information.
- The estimation technique described before can be integrated into the current FDM software aiming at extending the FDM capabilities – it would provide more information (give accurate analysis).



## 5. CONCLUSIONS

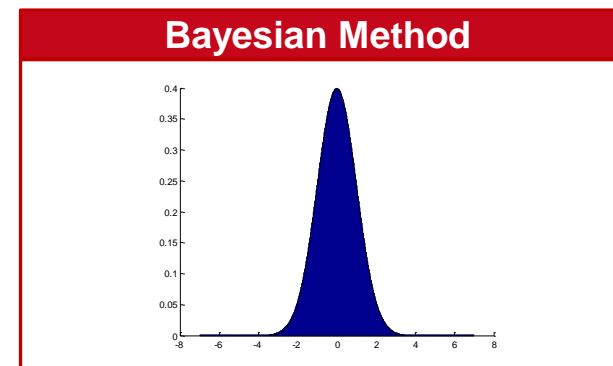
- The computation time took not more than 30 seconds for each flight phase. The computation time is highly depending on the number of measurements involved in the estimation process.
- Can be run on massive data but requires an algorithm for flight segmentation.

- It would be better to represent the parameters in distribution form instead of a single value. This is due to some contributing factors which makes QAR data has some uncertainties such as:
  - Untailored flight maneuver.
  - Low and different sampling rate.
  - Untailored control input.



$\theta$  = single value

VS



$\theta$  = distributed

Parameter distribution captures the uncertainties in the data.



## Lift Coefficient and Its Increment Due to Flap Deflection in Distribution Form

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# Thank you!

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## Professor

Florian Holzapfel ([florian.holzapfel@tum.de](mailto:florian.holzapfel@tum.de))

## PhD Students

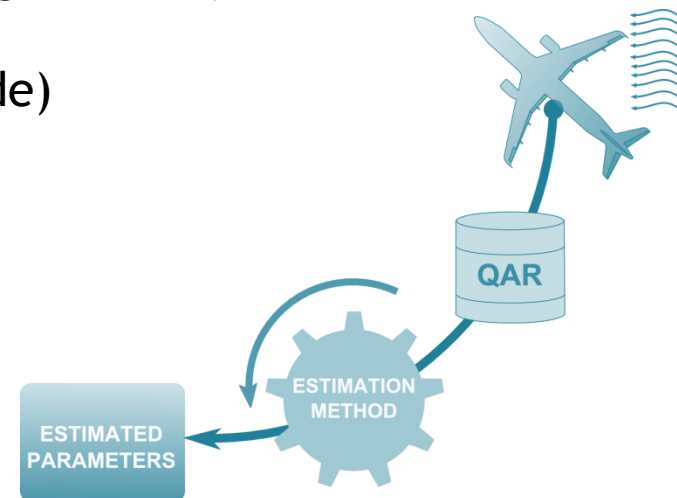
Javensius Sembiring ([javensius.sembiring@tum.de](mailto:javensius.sembiring@tum.de))

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# Additional Slides

# MAXIMUM LIKELIHOOD PRINCIPLE

$$\max \rightarrow p(\mathbf{z}|\boldsymbol{\theta}) = \frac{1}{(2\pi)^{\frac{n_y}{2}} \sqrt{|\mathbf{R}|}} e^{-\frac{1}{2} \sum_{k=1}^N [\mathbf{z}(t_k) - \mathbf{y}(t_k)]^T [\mathbf{R}]^{-1} [\mathbf{z}(t_k) - \mathbf{y}(t_k)]} \quad \dots (1)$$

or minimizing the – logarithmic of likelihood function:

$$J(\boldsymbol{\theta}) = (L(\mathbf{z}|\boldsymbol{\theta})) = -\frac{1}{2} \sum_{k=1}^N [\mathbf{z}(k) - \mathbf{y}(k)]^T [\mathbf{R}]^{-1} [\mathbf{z}(k) - \mathbf{y}(k)] + \frac{N}{2} \ln[\det(\mathbf{R})] + \frac{N n_y}{2} \ln(2\pi) \quad \dots (2)$$

$$\frac{\partial J(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} = \mathbf{0} \longrightarrow \left( \frac{\partial J(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right)_{i+1} \approx \left( \frac{\partial J(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right)_i + \left( \frac{\partial^2 J(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}^2} \right)_i \Delta \boldsymbol{\theta} = \mathbf{0} \quad \dots (3)$$

$$\Delta \boldsymbol{\theta} = - \left[ + \left( \frac{\partial^2 J(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}^2} \right)_i \right]^{-1} \left( \frac{\partial J(\boldsymbol{\theta})}{\partial \boldsymbol{\theta}} \right)_i \quad \dots (4)$$

$$\Delta \boldsymbol{\theta} = -\mathcal{F}^{-1} \mathcal{G} \quad \dots (5)$$

where:

$$\mathcal{F} = \sum_{k=1}^N \left[ \frac{\partial \mathbf{y}(t_k)}{\partial \boldsymbol{\theta}} \right]^T \mathbf{R}^{-1} \left[ \frac{\partial \mathbf{y}(t_k)}{\partial \boldsymbol{\theta}} \right]$$

$$\mathcal{G} = - \sum_{k=1}^N \left[ \frac{\partial \mathbf{y}(t_k)}{\partial \boldsymbol{\theta}} \right]^T \mathbf{R}^{-1} [\mathbf{z}(t_k) - \mathbf{y}(t_k)]$$

$\mathbf{z}$  = measurement/observation

$\mathbf{y}$  = output model

$n_y$  = number of output

$\mathbf{R}$  = matrix covariance

Parameters are updated by using equation (6) below:

$$\boldsymbol{\theta}_{i+1} = \boldsymbol{\theta}_i + \Delta \boldsymbol{\theta} \quad \dots (6)$$



# KINEMATIC EQUATIONS

- Kinematic equations are used for data compatibility check aiming at determining the bias error or scale factor which might exist in the measurements.

## State Equations:

$$\begin{aligned}\dot{V} &= (\hat{a}_x \cos \alpha + \hat{a}_z \sin \alpha) \cos \beta + \hat{a}_y \sin \beta + \\ &\quad g(\cos \theta \cos \phi \sin \alpha \cos \beta + \cos \theta \sin \phi \cos \beta - \sin \theta \cos \alpha \cos \beta) \\ \dot{\alpha} &= \frac{1}{V \cos \beta} [\hat{a}_z \cos \alpha - \hat{a}_x \sin \alpha + g(\cos \theta \cos \phi \cos \alpha + \sin \theta \sin \alpha)] + \hat{q} \\ &\quad - \tan \beta (\hat{p} \cos \alpha + \hat{r} \sin \alpha)\end{aligned}\quad (1)$$

$$\begin{aligned}\dot{\beta} &= \frac{1}{V} [\hat{a}_y \cos \beta - (\hat{a}_x \cos \alpha + \hat{a}_z \sin \alpha) \sin \beta + \\ &\quad g(\cos \theta \sin \phi \cos \beta + (\sin \theta \cos \alpha - \cos \theta \cos \phi \sin \alpha) \sin \beta)] + \hat{p} \sin \alpha - \hat{r} \cos \alpha\end{aligned}$$

$$\dot{\phi} = \hat{p} + \hat{q} \sin \phi \tan \theta + \hat{r} \cos \phi \tan \theta$$

$$\dot{\theta} = \hat{q} \cos \phi - \hat{r} \sin \phi$$

$$\dot{\psi} = \hat{q} \sin \phi \sec \theta + \hat{r} \cos \phi \sec \theta$$

where,

$$\hat{a}_x = a_{xm} - \Delta a_x \quad \hat{p} = p_m - \Delta p$$

$$\hat{a}_y = a_{ym} - \Delta a_y \quad \hat{q} = q_m - \Delta q$$

$$\hat{a}_z = a_{zm} - \Delta a_z \quad \hat{r} = r_m - \Delta r$$

## Measurement Equations:

$$\begin{aligned}V_m &= V + \Delta V & \phi_m &= \phi + \Delta \phi \\ \alpha_m &= K_\alpha \alpha + \Delta \alpha & \theta_m &= \theta + \Delta \theta \\ \beta_m &= K_\beta \beta + \Delta \beta & \psi_m &= \psi + \Delta \psi\end{aligned}\quad (2)$$

## Parameters to be Estimated:

$$\Theta = [\Delta a_x \Delta a_y \Delta a_z \Delta \phi \Delta \theta \Delta \psi \Delta p \Delta q \Delta r \Delta V \Delta \alpha \Delta \beta K_\alpha K_\beta]^T \quad (3)$$





# POSTULATED MODEL FOR AERODYNAMIC ESTIMATION

$$\hat{a}_x \approx \frac{1}{mg} (\bar{q} S C_X + T)$$
$$\hat{a}_z \approx \frac{1}{mg} (\bar{q} S C_Z)$$

... in body axes (1)

aerodynamic model

$$C_L = C_{L_0} + \Delta C_L$$
$$C_D = C_{D_0} + \Delta C_D$$

(3)

$\hat{a}_x, \hat{a}_z$ , and  $\hat{\alpha}$  are obtained from Data Compatibility Check.

$$C_L = -C_Z \cos \hat{\alpha} + C_X \sin \hat{\alpha}$$
$$C_D = -C_X \cos \hat{\alpha} - C_Z \sin \hat{\alpha}$$

... in wind axes (2)