FMRA
Fachgebiet Flugmechanik, Flugregelung und Aeroelastizität

PILOT MODEL FOR WAKE VORTEX ENCOUNTER SIMULATIONS FOR TAKEOFF AND DEPARTURE

Berlin Institute of
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WakeNet3 - Europe Specific Workshop: Models and Methods for WVE Simulations

- **Motivation**

  Risk analysis in with Monte Carlo

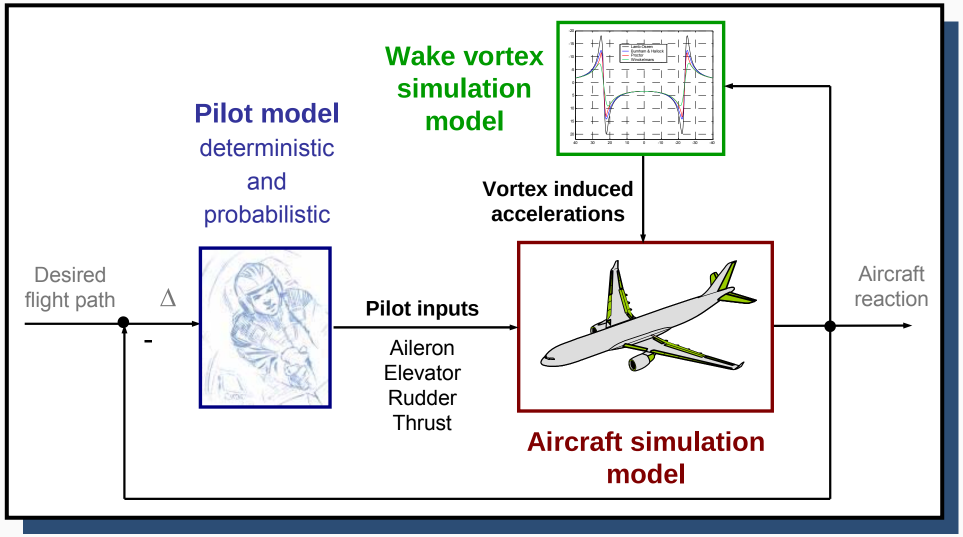
  Simulation (MCS)

  Application: Wake Vortex Encounter (WVE)

  ➡ Models needed:

  - Aircraft
  - Vortex (Evolution, Interaction)
  - **Pilot behaviour**

Elements of MCS



- **Objective**

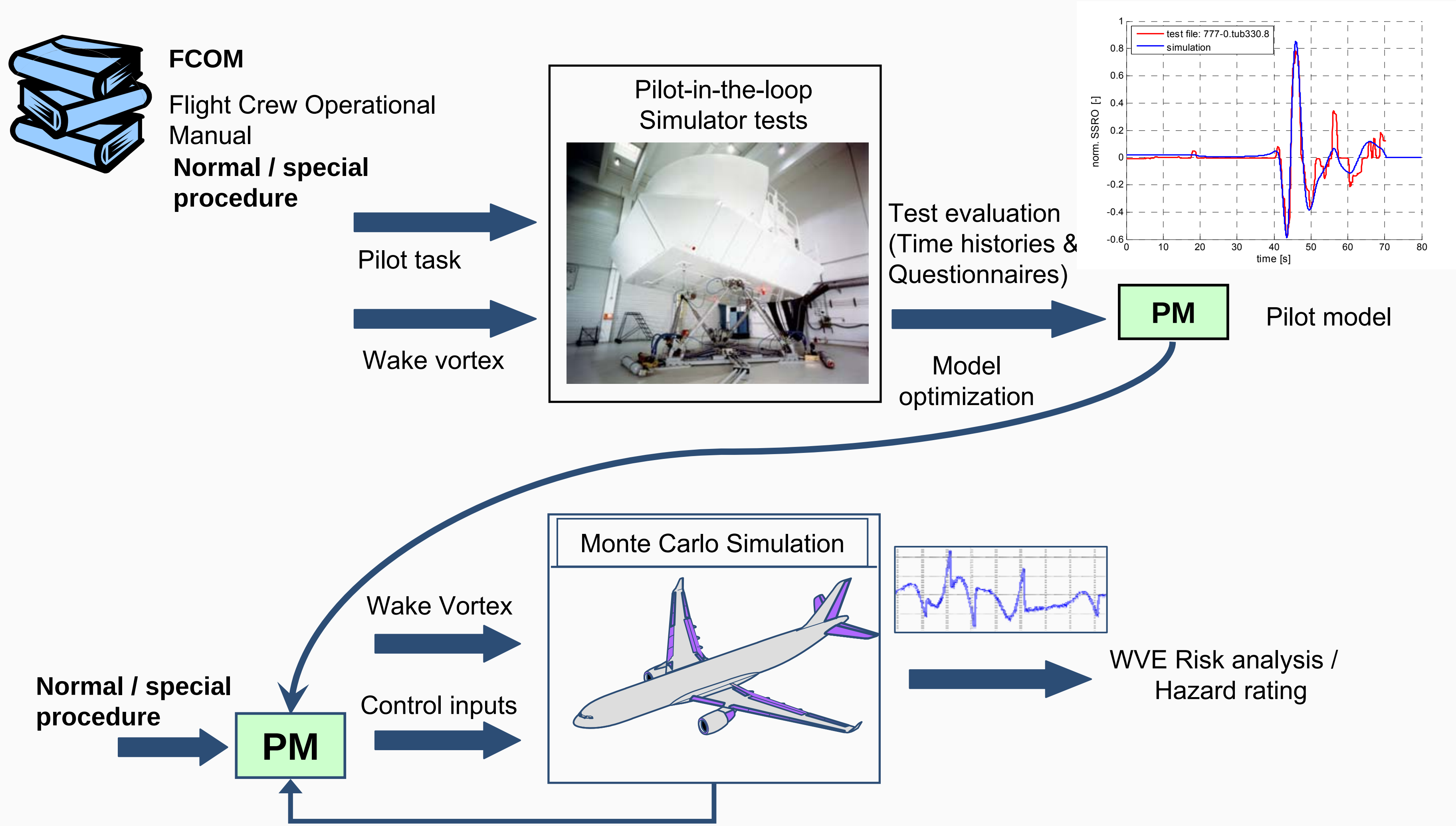
  o Modelling of human pilot behaviour for tracking and WVE recovery

  o Validated pilot model

Content

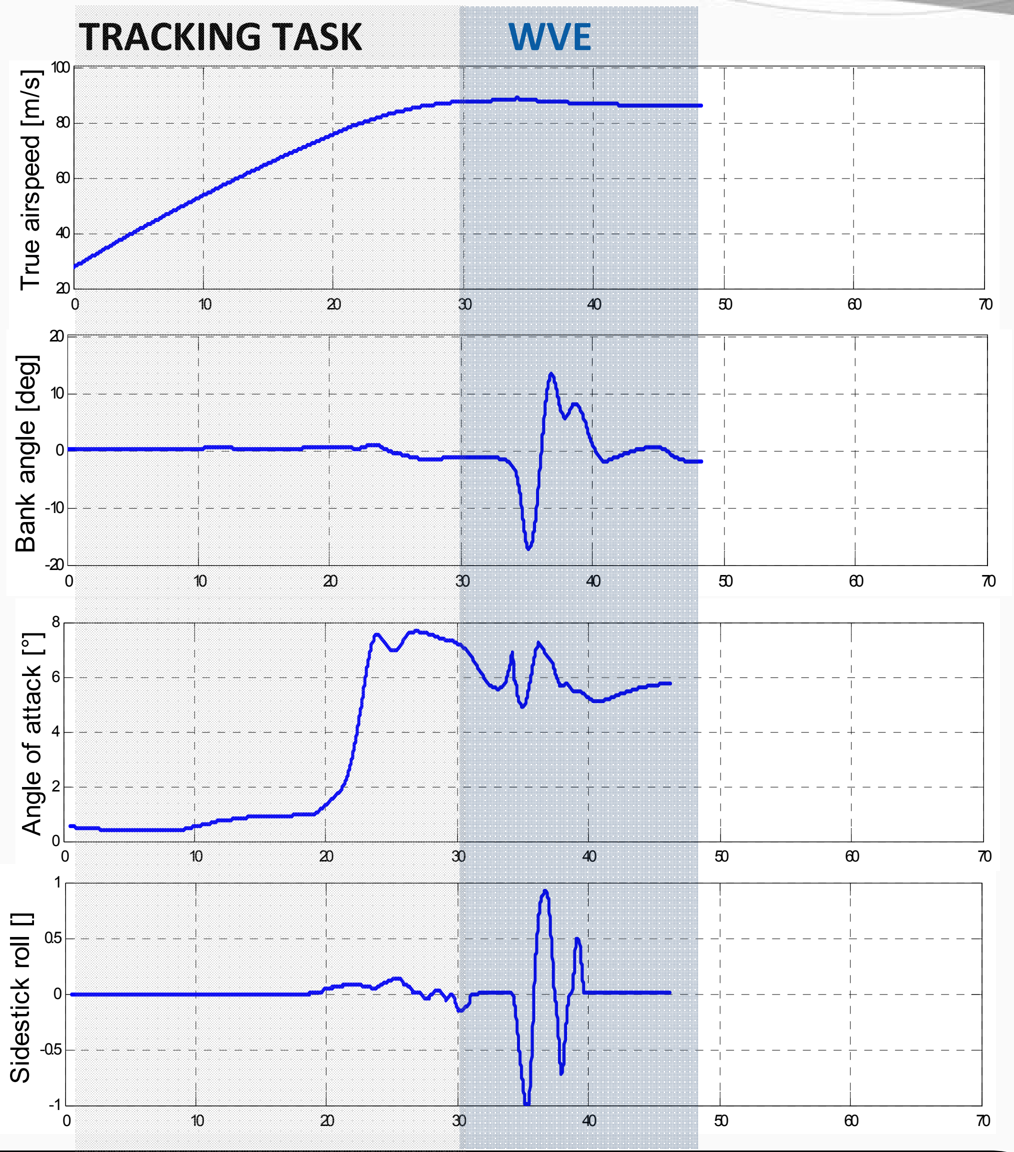
- Development process
- Simulator data for pilot modelling
- Structure of pilot model
- Neural network part of pilot model
    - o Topology
    - o Parameter optimisation
- Validation
- Conclusion

Development process and application



Flight phases to model

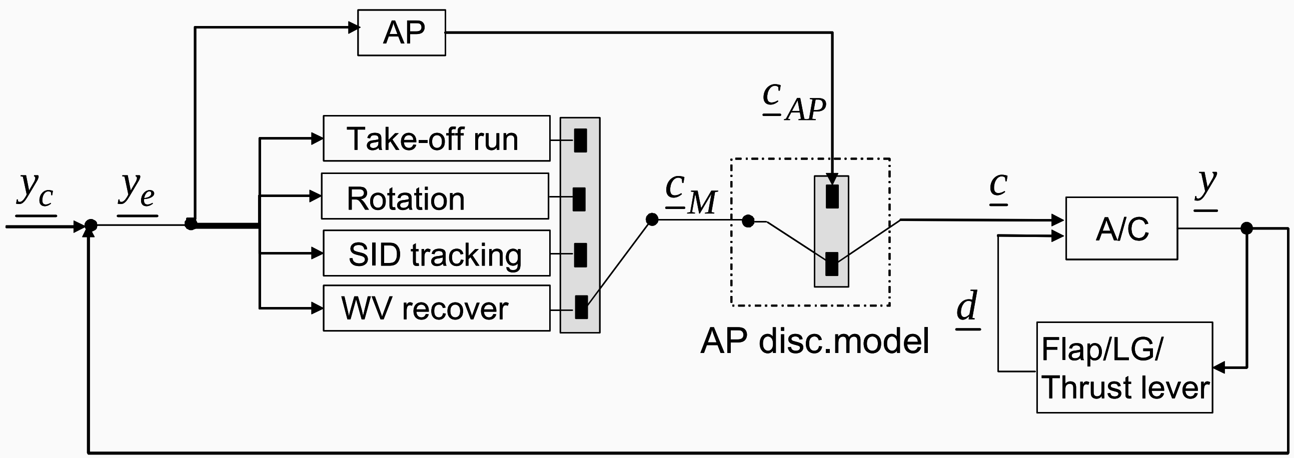
CONTROL TASK
Take-off run on the runway centre line
Rotation
Climb along the desired flight path
Correct lateral deviations
Match the stationary aircraft climb gradient to the actual thrust level
Retract flaps, landing gear and reduce thrust setting depending on altitude and speeds
Stabilize the a/c after encountering a wake vortex
Disconnect AP in case of high deviation from the nominal flight path



➡ The variety of tasks requires a pilot model consistent out of many submodules

Pilot model

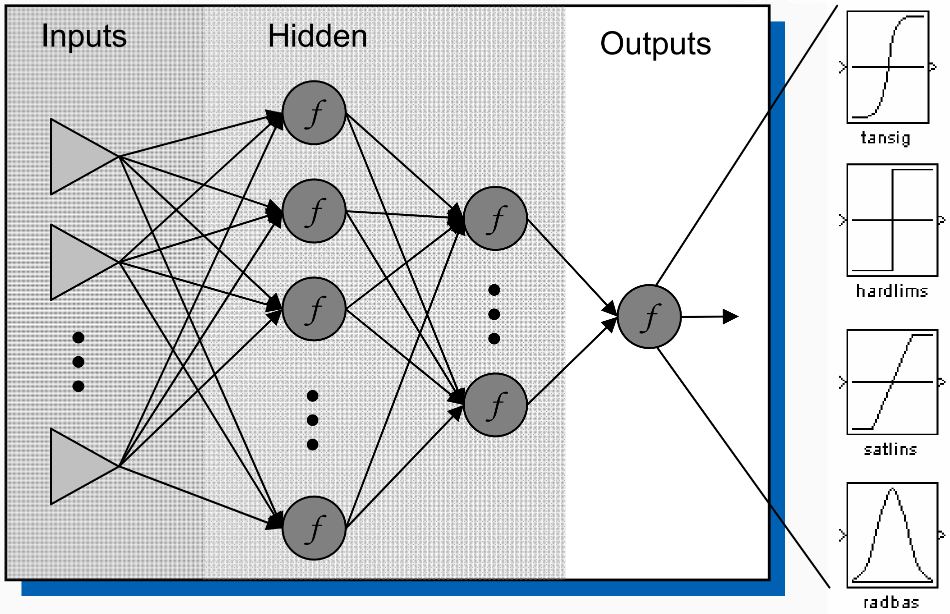
CONTROL TASK	SUB-MODULE	OUTPUT (CONTROL ELEMENT)
Take-off run on the runway centre line	Take-off run	Pedal position
Rotation	Rotation	Sidestick pitch
Climb along the desired flight path	SID tracking	Sidestick pitch Sidestick roll
Correct lateral deviations		
Match the stationary aircraft climb gradient to the actual thrust		
Retract flaps, landing gear and reduce thrust setting depending on altitude and speeds	Flap, landing gear, thrust lever control	Throttle lever (TL) Flap lever (FL) Landing gear lever (LGL)
Stabilize the a/c after encountering a wake vortex	Wake vortex recovery	Sidestick pitch Sidestick roll
Disconnect AP in case of high deviation from the flight path	AP disconnect model	AP disconnect button



Neural network

- **Model approaches**
  - static feed-forward network
  - recurrent network

- **Design parameters (Topology)**
  a) number/ choice of inputs
  b) number of layers
  c) type of activation function



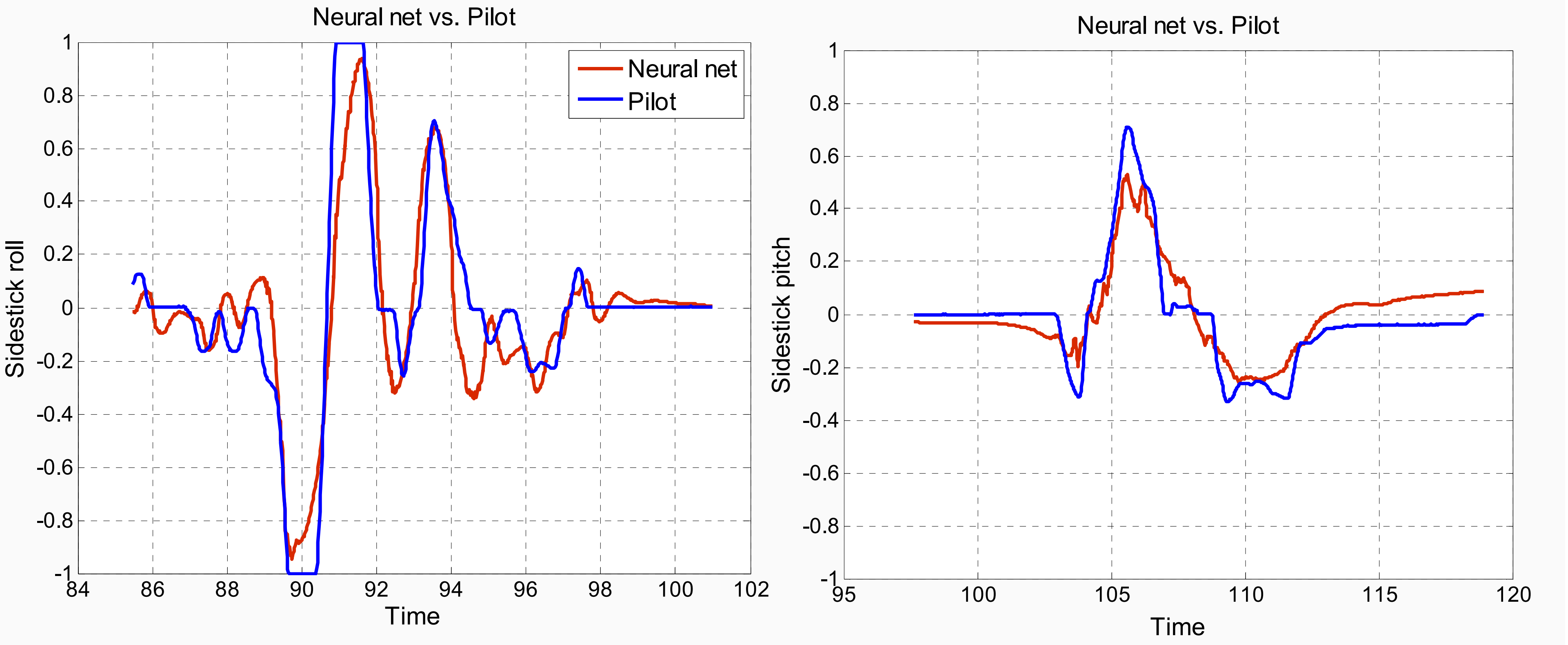
- **Training**
  - backpropagation with Matlab (cost function=MSE)
  - optimization with MOPS (user-defined cost function), post-processing

    Problems: time-consuming calculation for evolutional algorithm because of the high number of parameters (tuners) in neural networks

  -stops training by the use of cross validation

    → division of simulator data: 60% training, 20% validation, 20% test data

Evaluate net performance

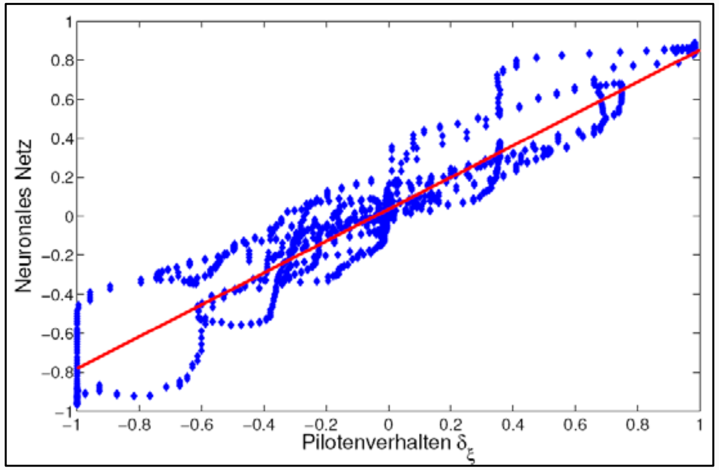


Mean square error *MSE*

$$MSE = \frac{\sum_{n=1}^{N}\left(y^*(n) - y_k(n)\right)^2}{N}$$

y^*	recorded human pilot outputs
y_k	neural network modelled outputs
N	number of data samples

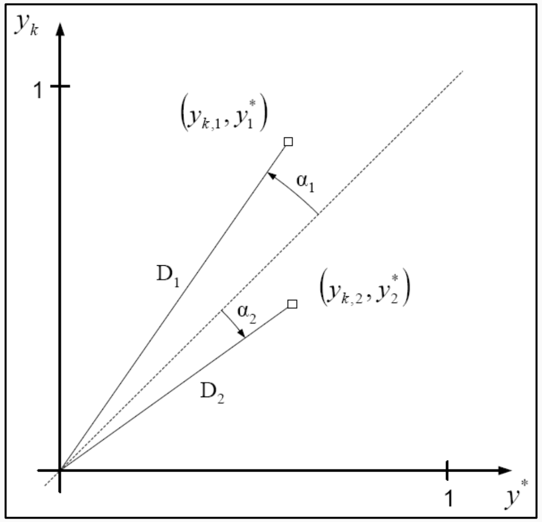
Correlation coefficient



Average Angle Measure *AAM*

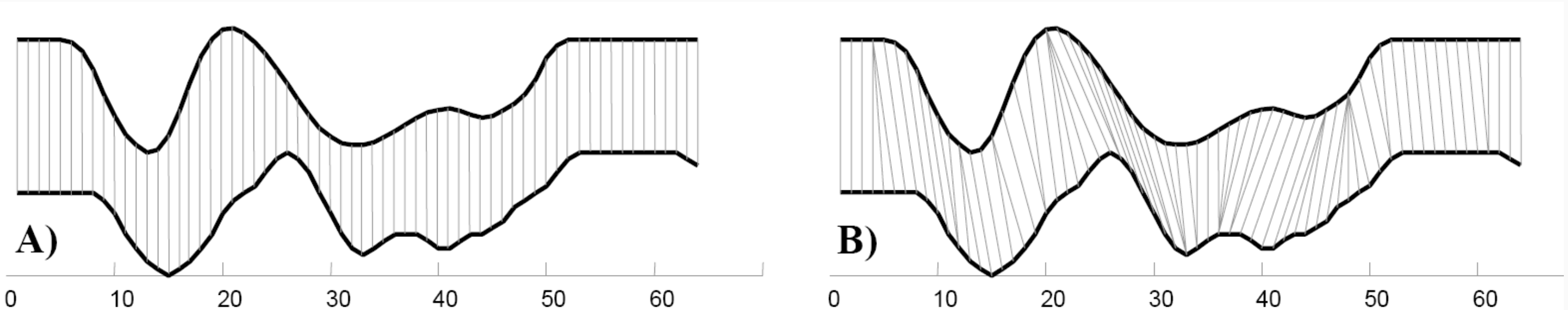
$$AAM = 1 - \frac{4}{\pi}\left[\frac{\sum_{n=1}^{N} D(n)\cdot|\alpha(n)|}{\sum_{n=1}^{N} D(n)}\right];$$

$$\alpha(n) = \arccos\left[\frac{\left|y^*(n) + y_k(n)\right|}{\sqrt{2}D(n)}\right]; \quad D(n) = \sqrt{y^*(n)^2 + y_k(n)^2}$$



Dynamic Time Warping (DTW)

- Using dynamic time warping to find patterns in time series
- Algorithm for measuring similarity between two sequences which may vary in time and speed → Sequences are warped non-linearity in the time dimension
- Measure of their similarities independent of certain non-linear variations in the time dimension
- Target: Find the optimal alignment between two time series, which minimizes the sum of distances between aligned elements



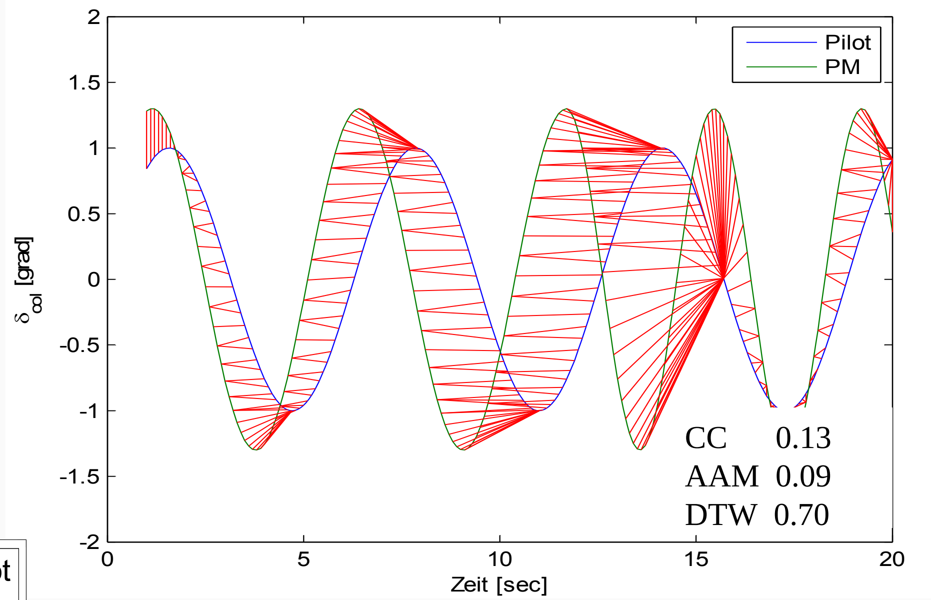
- While sequences have an overall similar shape, they are not aligned in time axis

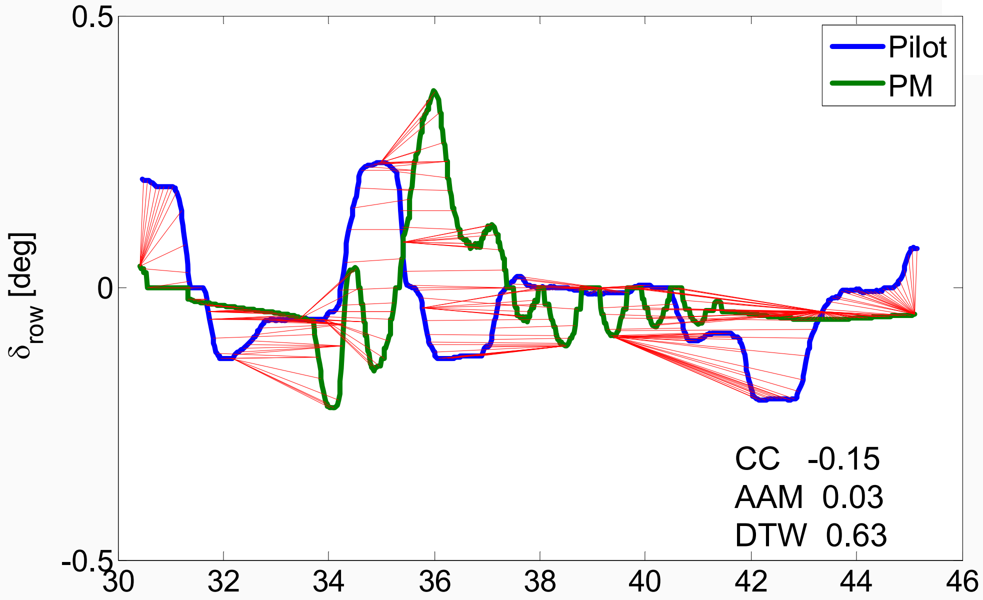
Evaluate net performance

Dynamic Time Warping

Synthetic case: demonstrate differences between evaluation criteria

- two sinus signals, differ in amplitude and time
- No similarity given by CC= 0.13 and AAM=0.09
- The DTW= 0.7 implies a reasonable similarity



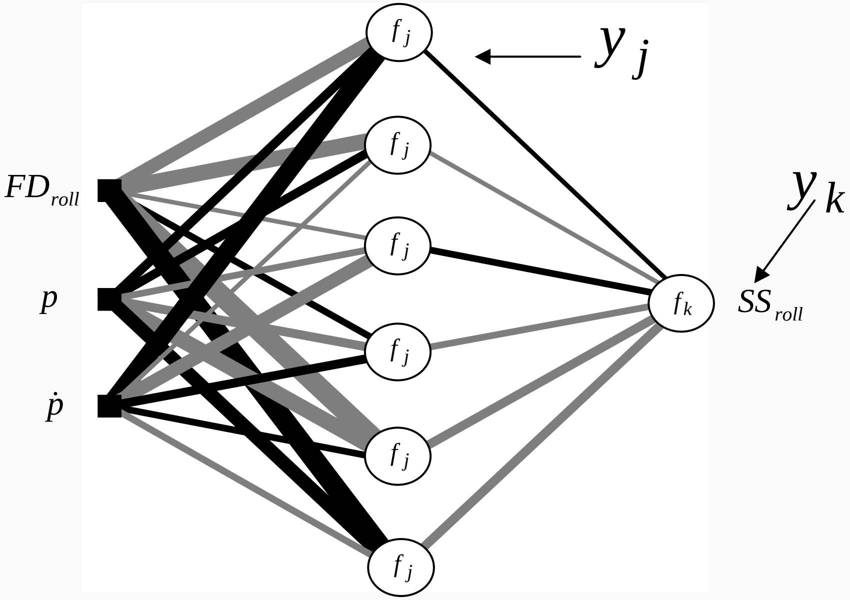


Real case:

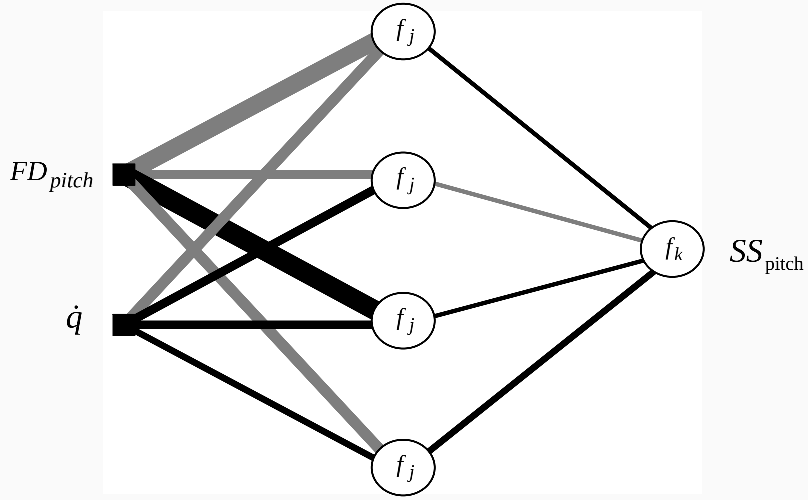
- E.g. phenomenon of variable time delayed reaction
- No similarity given by CC= -0.15 and AAM=0.03
- The DTW= 0.63 implies a reasonable similarity

Chosen net topologies

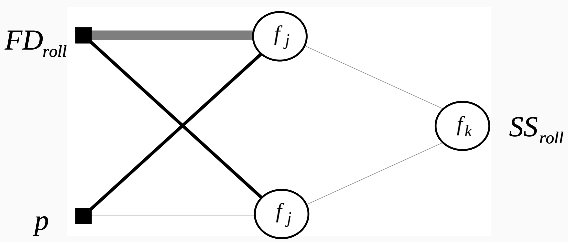
WVE Mode: Roll axis



WVE Mode: Pitch axis



Tracking Mode: Roll axis



Functionality of a neuron

$$z_j = b_j + \sum_{i=1}^{l} (x_i \cdot w_{ji}),$$

$$y_j = f_j(z_j)$$

Neural net output signal

$$y_k = z_k = b_k + \sum_{j=1}^{m} (y_j \cdot w_{kj}),$$

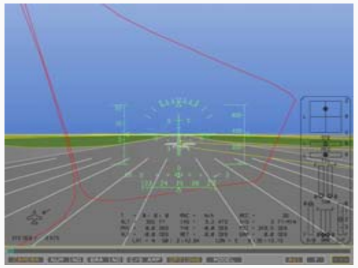
- **Online Validation**
  - A330 simulator (Berlin)
  - A320 simulator (Hamburg)

Pilot task

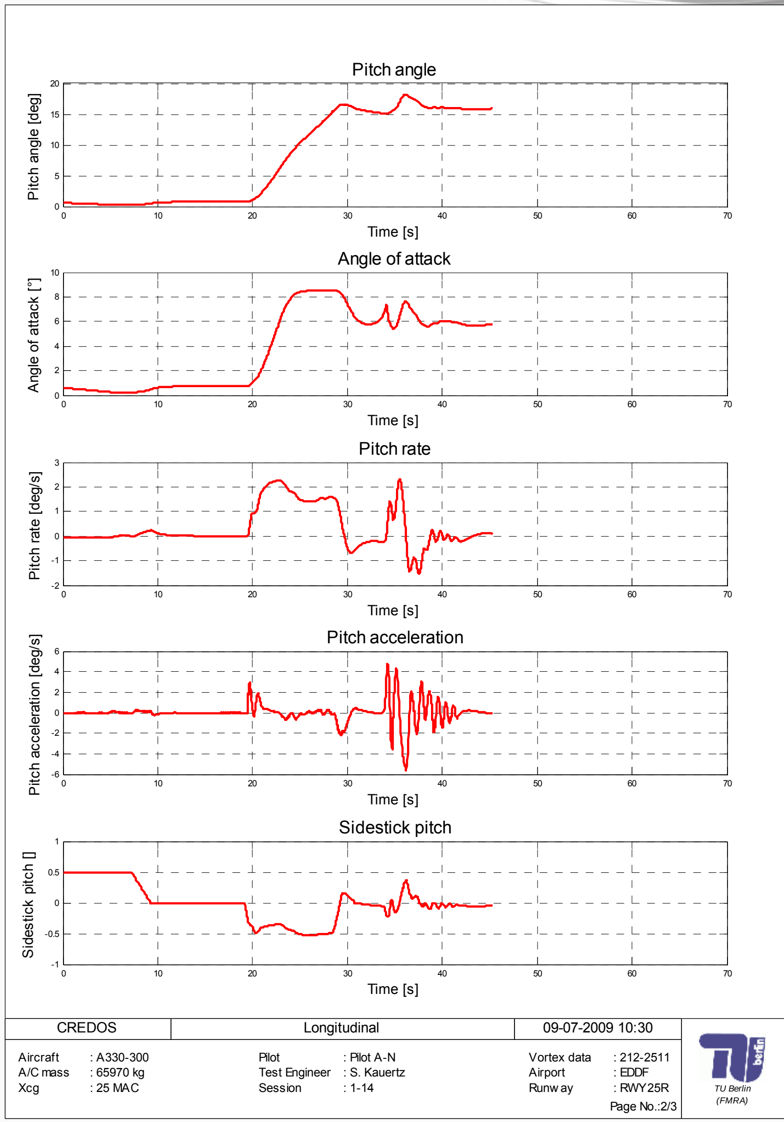
Wake vortex (repeatable “fixed encounter”)

Pilot-in-the-loop Simulator tests

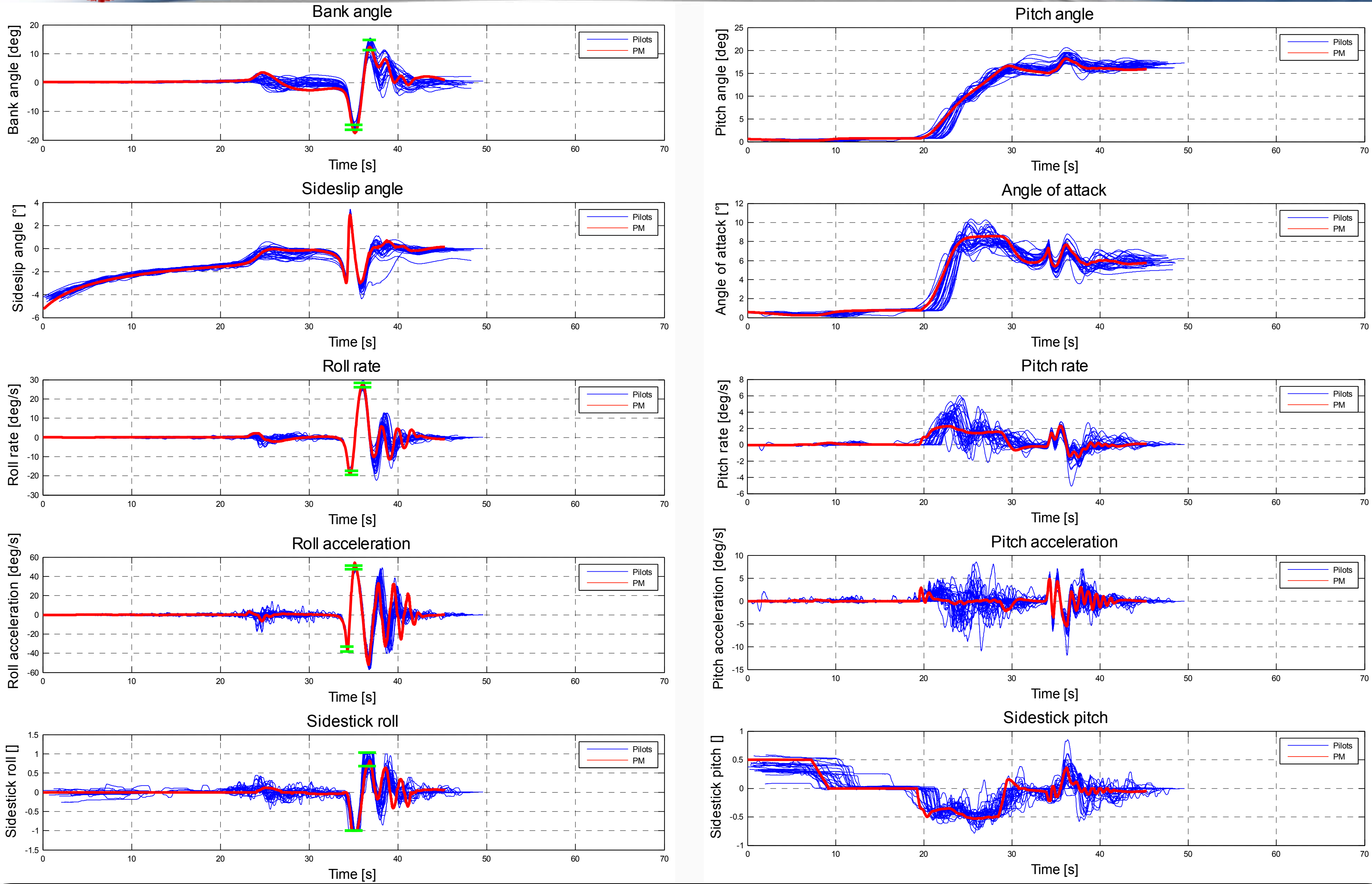
PM-in-the-loop Simulator tests



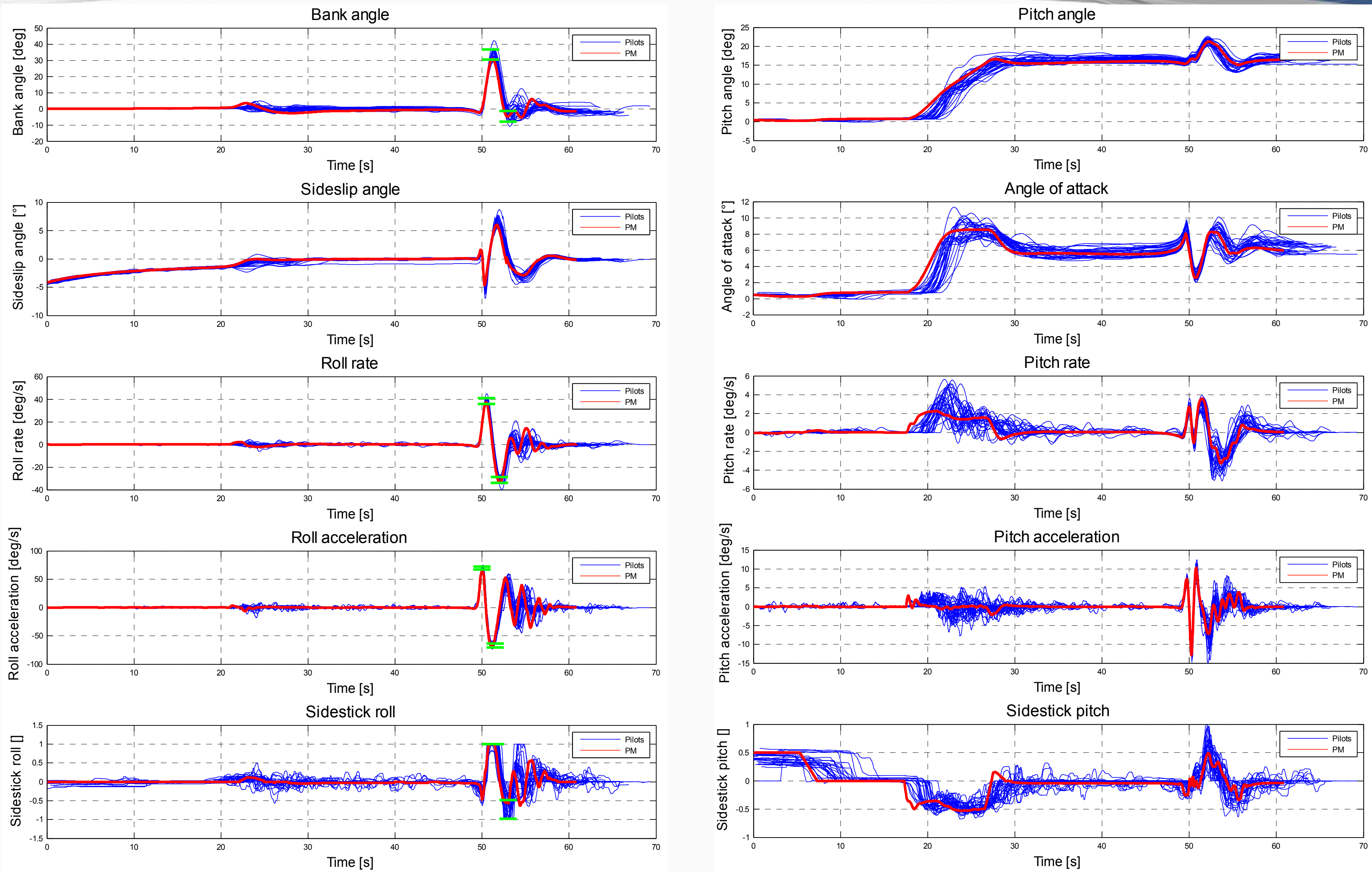
Time histories: A/C state



Validation PM-in-the-Loop



Validation PM-in-the-Loop



Conclusion

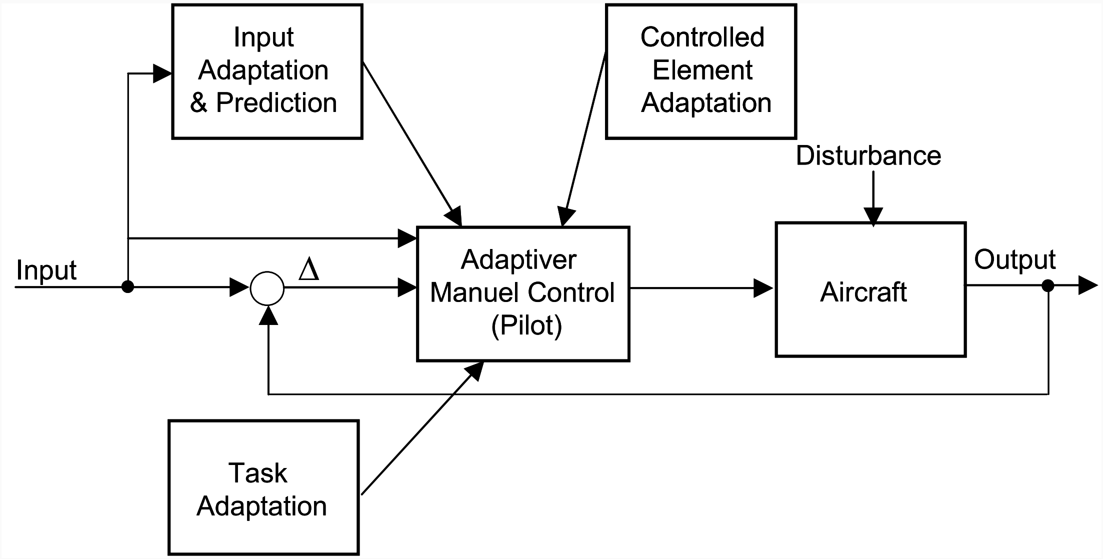
- Successful implementation of the pilot model into the A320 simulation
- A very good agreement between human pilot and PM (on the basis of a feed-forward neural network) behaviour was achieved in the roll axis
- The deterministic pilot model lies, in most of the cases, inside the standard deviation of human pilots for sidestick roll, roll rate, roll acceleration and bank angle
- The PM based on recurrent networks delivered comparable good results
- The general structure for a PM probabilistic add-on is considered in the A320 simulation

Present activities

Adaptive Pilot Model

- **Motivation/ Idea**
  - o Approximate human pilot adaptation abilities between tracking- and compensatory tasks

- **Objective**
  - o Only one model for tracking tasks AND compensatory tasks
  - o no discrete switches, avoid possible instable aircraft reactions



Adaptive Pilot Model

- **Approach**
  - o Applied on a controlled aircraft (VFW-614) simulation
  - o Adaptive part is described by a neural networ
  - o Human pilots diversity
    - needed for statistical investigations
    - can be covered by different learning rates, required precision of adaptation, variations in time delay for input and output data of the neural net
  - o An extension on a predictive module (Luenberger observer, Kalman filter, or 2nd neural net) is intended
  - o The model should be applicable at least for real-time simulations

- **Problems**
  - o Differences between open-loop (static) and closed-loop (dynamic simulation) neural net training
  - o Closed-loop adaptation is highly learning rate (gradient) sensitive (aircraft instability)
  - o Training epoch > 1
  - o Dead time compensation is needed (error of cost function and inputs contains the dead time of a/c, actuator, sensor, etc)
  - o Predictive part still missing