Mid term conflict resolution: A Model Predictive Control Approach

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Credits

- ETH
  - G. Chaloulos
- National Technical University of Athens
  - K. Kyriakopoulos
  - G. Roussos
- University of Cambridge
  - J. Maciejowki
  - E. Siva

http://ifly.nlr.nl/

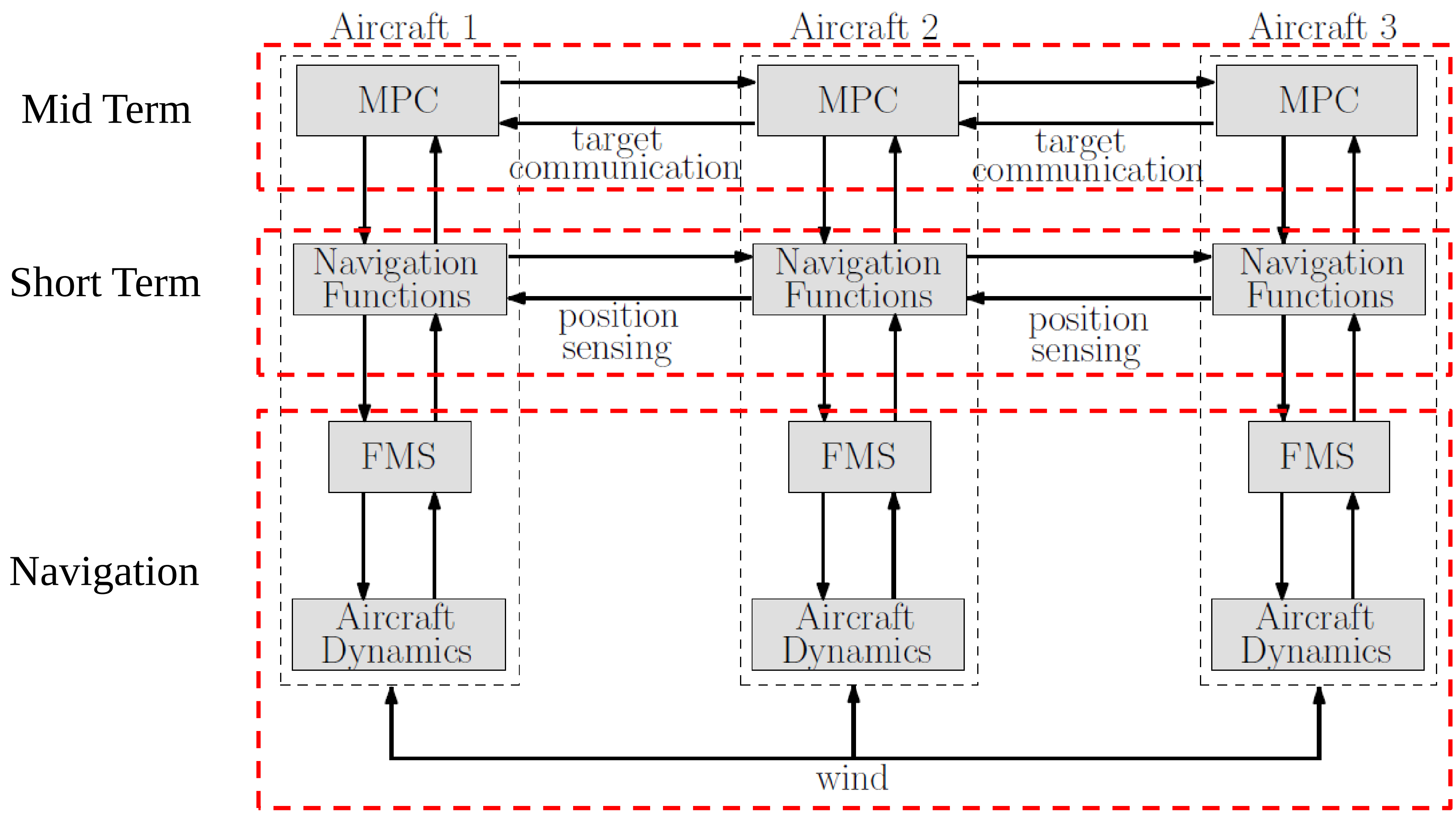
Short term CR

- Short Term CR algorithms should
  - Be fast, as they should resolve conflicts in minutes
  - Guaranteed conflict avoidance, last CR layer
  - Decentralized in self-separation airspace
- Example: Navigation functions
  - Guaranteed convergence and conflict avoidance
  - Computationally efficient
  - Decentralized fashion, implicit coordination
  - Closed loop, account for disturbances and errors

Difficulties

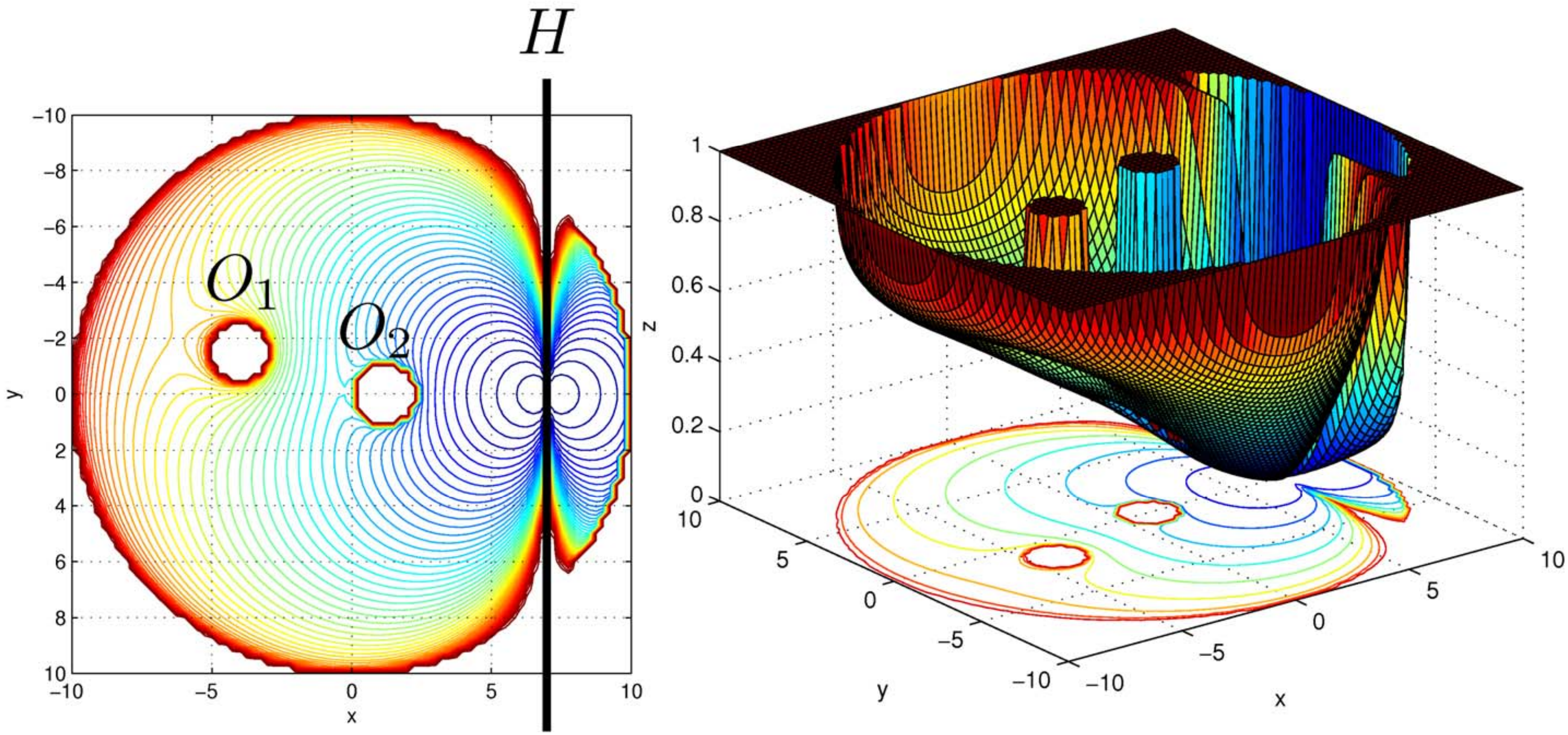
- Short term horizon source of complications
- Guaranteed resolution may require large inputs
  - Speed changes, rates of turn, …
- More difficult to optimize "secondary" objectives
  - Fuel consumption, delay, passenger comfort, …
- More difficult to provide alternatives
  - Alternative resolution maneuvers for crew to select
- Etc.
- Longer preview may help with all of these

Hierarchical approach

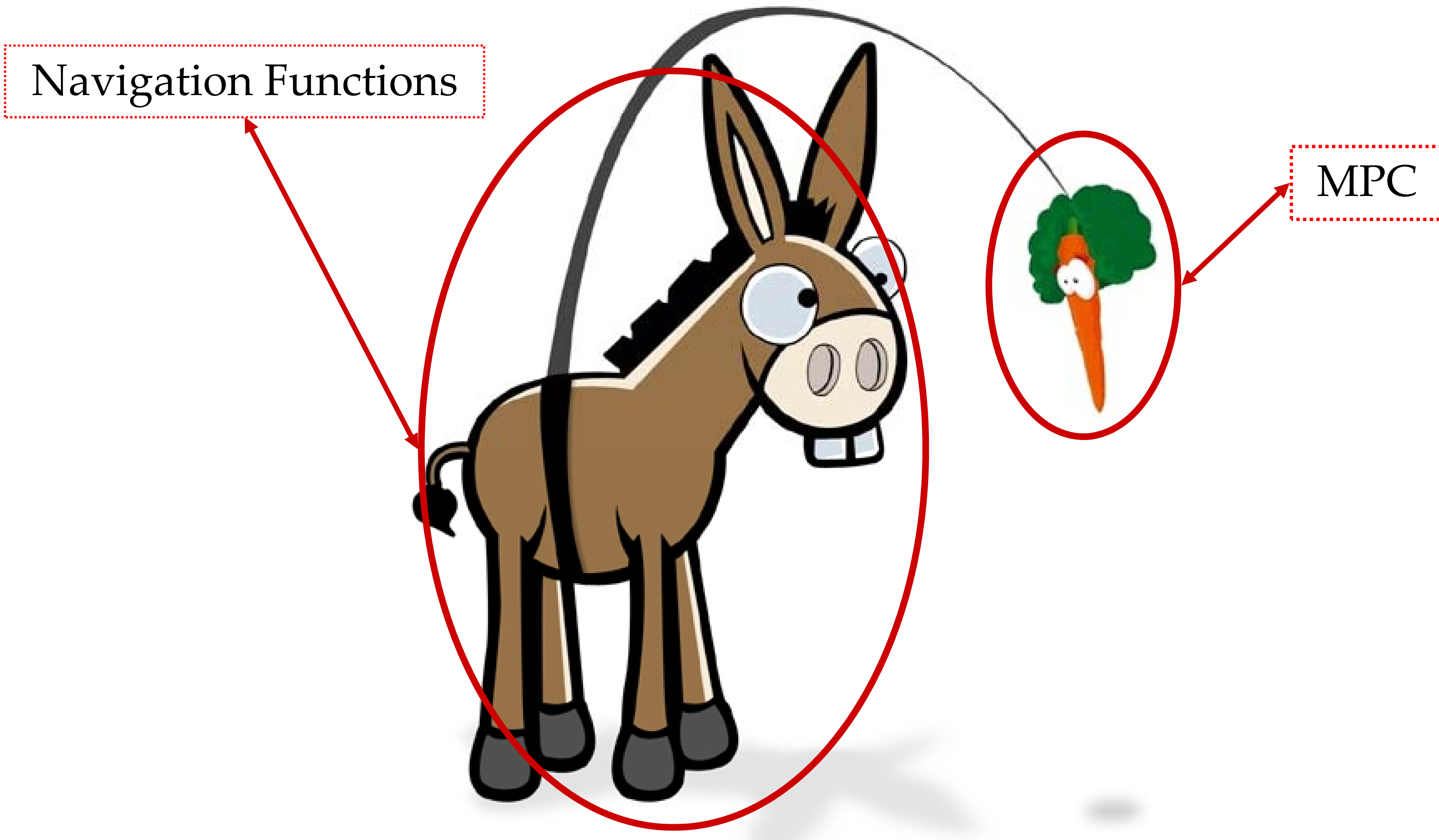


Navigation Functions

- Build artificial potential using measured aircraft positions and destination information



Preview by Model Predictive Control



MPC algorithm

1. Measure aircraft positions
2. Use a model to predict the future
   - Say for the next 20 minutes
   - Taking into account actions of short term CR
3. Formulate an optimization problem to
   - Minimize cost (fuel, delay, …)
   - Impose constraints (speed, turning, passenger comfort)
   - Satisfy aircraft dynamics
4. Compute optimal solution
5. Apply first part (say first 3 minutes)
6. Return to 1 and repeat

Several proposals in the literature

- Centralized:
  - [Feron et.al.], [El Ghaoui, Duong et.al]
  - Implicit in long-term methods of [Bertsimas, Odoni et.al.], [Castelli et.al.]
- Decentralized:
  - [Richards & How], [Boreli, Balas et.al.], [Dunbar & Murray], [Bitmead et.al.]
  - [Raimondo, Scattolini, et.al.]
  - [Hiskens, Rawling et.al.], [Negenborn, de Schutter]
  - [Maciejowski & Siva]
  - [Roussos, Chaloulos, Kyriakopoulos, Lygeros]

Advantages

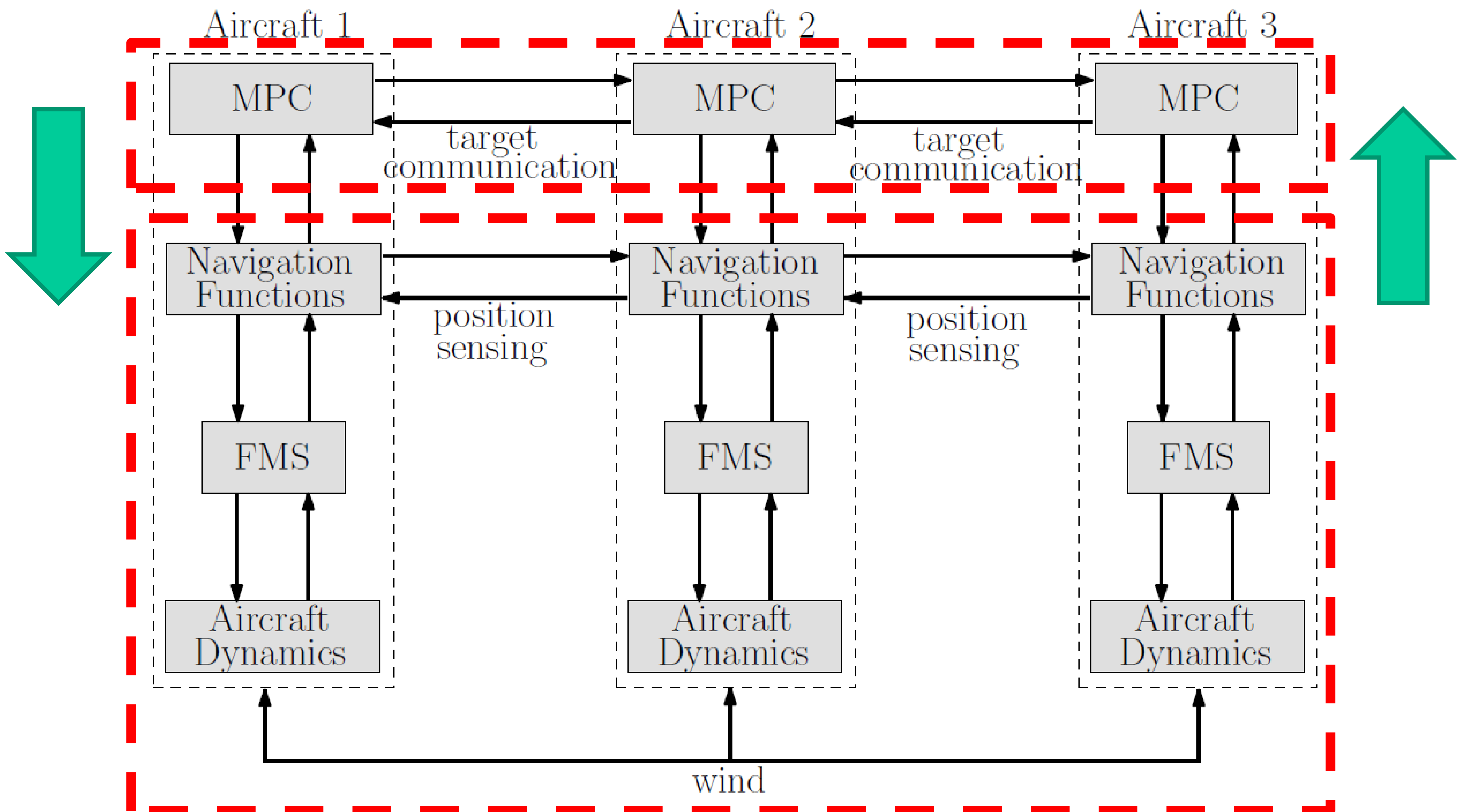
- Flexibility in optimization problem formulation
- Cost can reflect range of considerations
  - Fuel, delays, human factor preferences
- Constraints can reflect range of considerations
  - Aircraft dynamics, input constraints
  - Passenger comfort
- Integrate intent information, priorities, …
- Short term CR actions can be integrated in model
- Repeated measurements provide feedback
  - Correct for disturbances and errors (e.g. in model)

Difficulties

- Formulation of optimization problem an art
- Resulting optimization problem difficult to solve
  - Non convex due to collision avoidance requirement
  - Complicated further by dynamic nonlinearities, …
  - And by integration of short term CR actions
- Decentralization for self separation concepts
  - Optimize separately and communicate solutions
  - Formulate optimization problem of each aircraft
  - How to take effect on others into account?
  - How to provide performance (e.g. collision avoidance) guarantees?
  - Robust optimization, conservatism, …

Our approach

- Model taking lower hierarchy levels into account



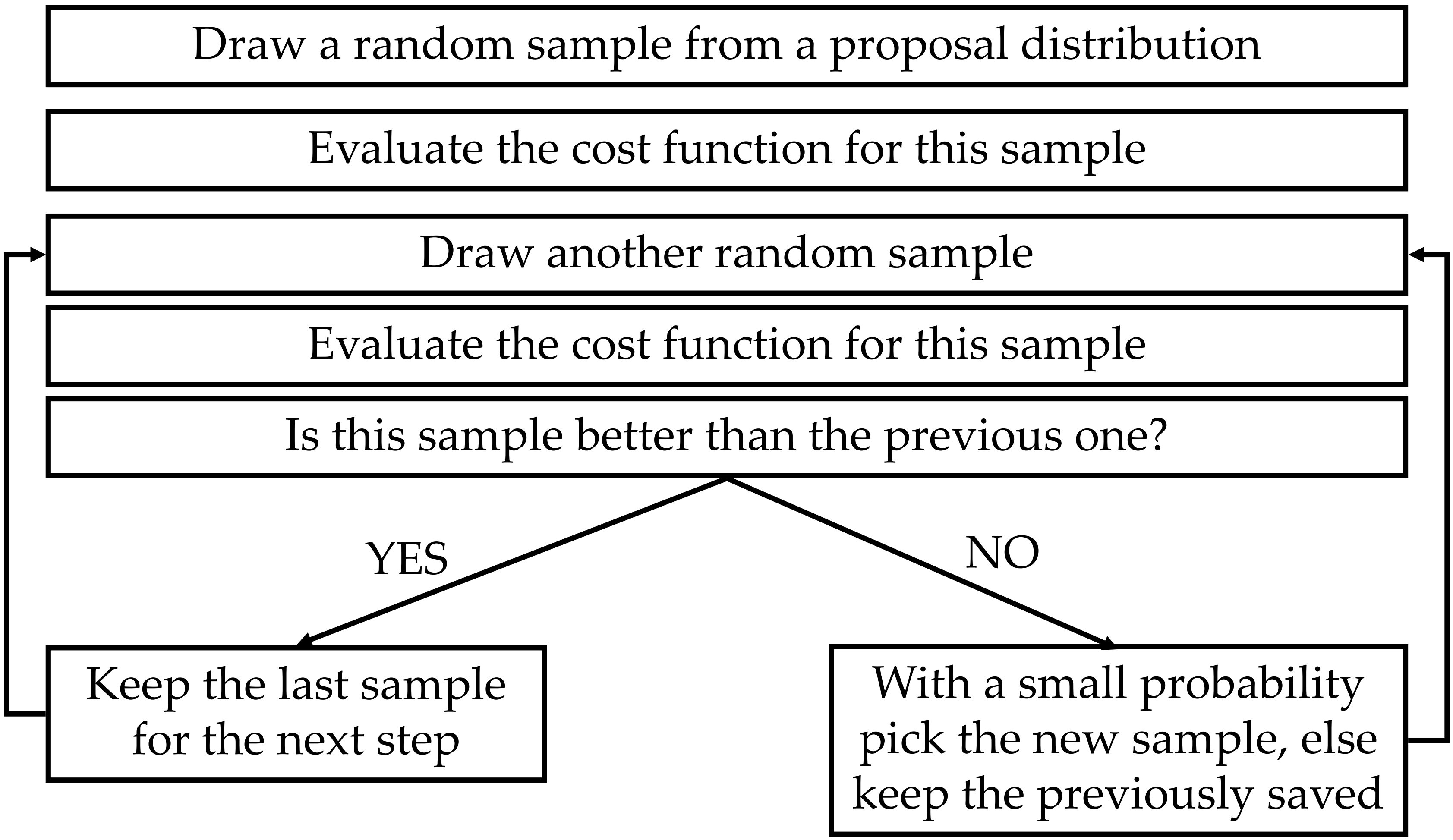
Our approach

- Predict (21 minutes) into the future
- Formulate optimization problem
  - Decision variables: Targets of navigation functions
  - Cost: Deviation from track
  - Constraints: Speed and turning radius bounds
- Solve, give resulting target to navigation function
- Fly for 3 minutes
  - Navigation function feedback
- Measure positions and repeat
  - Model Predictive Control feedback

Our approach

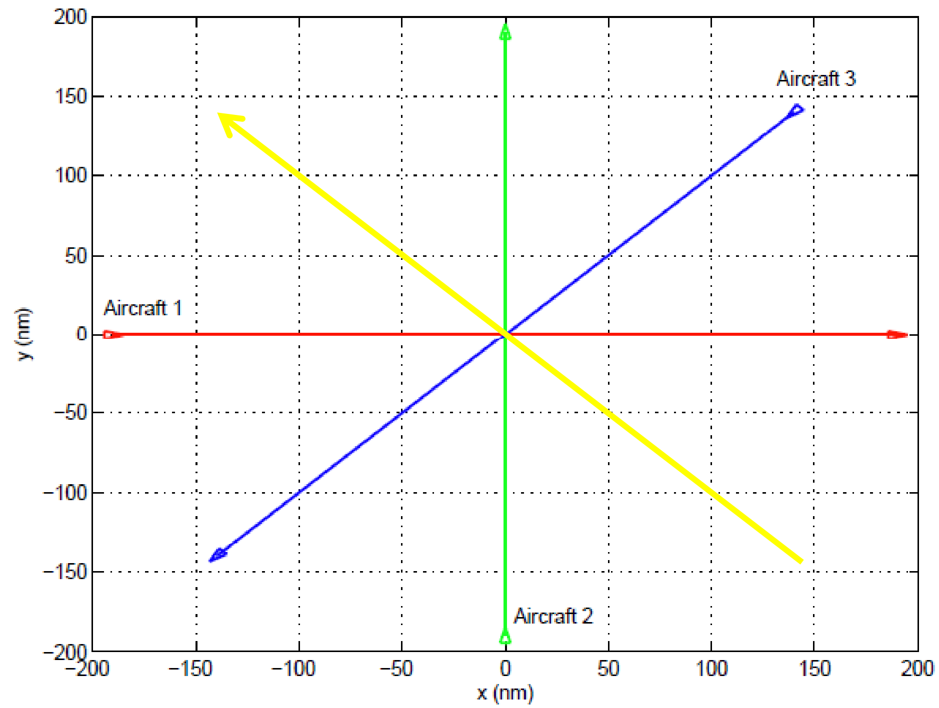
- Resulting optimization problem very difficult
  - Non convex due to collision avoidance constraint
  - Navigation model very complex
  - Can, however, be easily simulated
- Randomized optimization algorithm
  - Randomly select proposed target
  - Evaluate by simulation
  - Accept or reject based on performance
  - Repeat
- Evaluate on simulation with stochastic wind
  - Monte-Carlo simulation
  - Can also be introduced in randomized optimization

Randomized Optimization



Simulation Setup

- Several aircraft converging to the same point
- Aircraft try to reach as close as possible to their destination at the end of the 21mins horizon

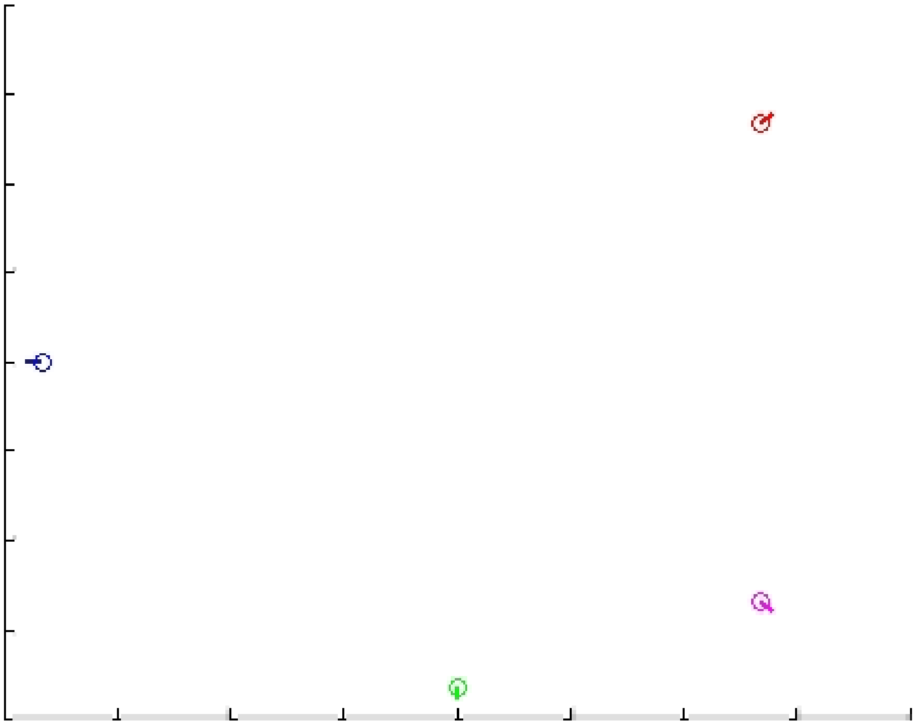


- Every 3 minutes algorithm searches for the optimal intermediate targets for the next 21 minutes
- Searching often enough and look-ahead time of ~20 minutes needed to avoid infeasibility

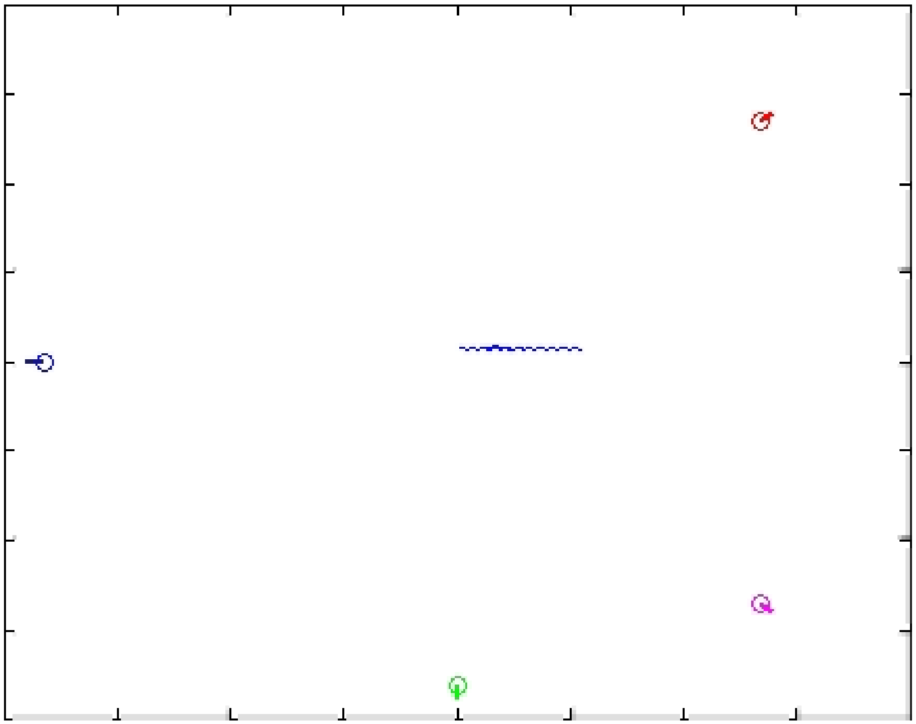
Simulation Results

- Constraint handling (cost incurring only for violating the speed constraints):

Without MPC



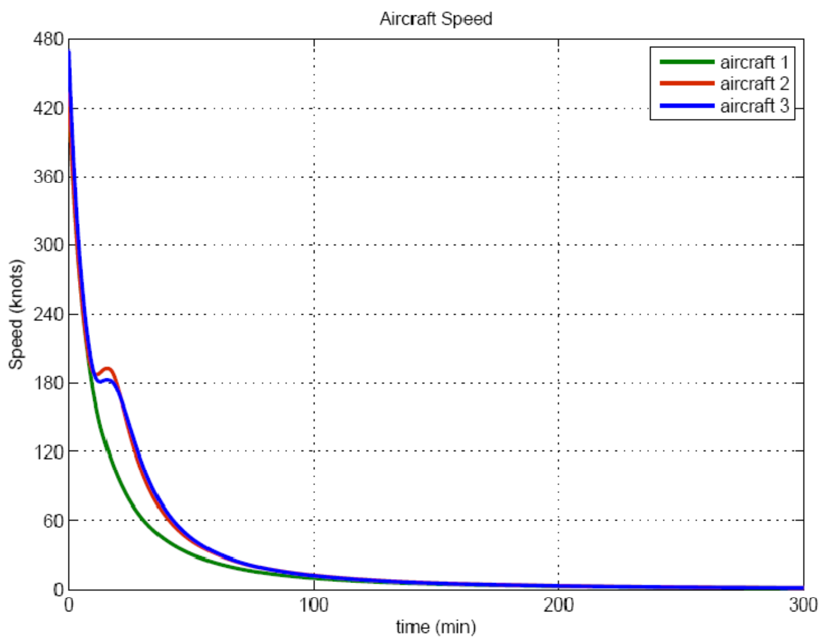
With MPC



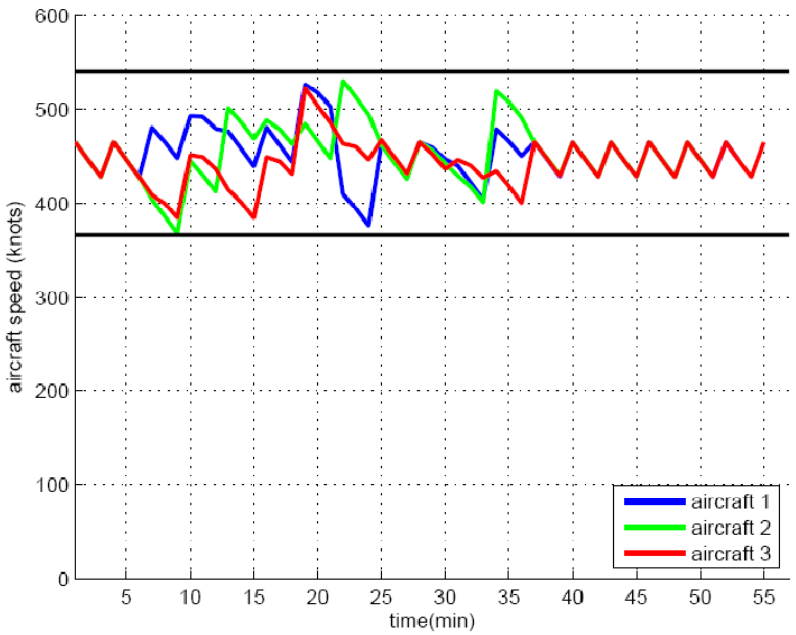
Simulation Results

- Aircraft speeds for the two cases:

Without MPC



With MPC



Decentralized MPC

- Aircraft solve individual MPC problems in round-robin
- Separate cost function and constraints for each aircraft
- First aircraft
  - Ignores future actions of other aircraft
  - Computes its solution, announces to other aircraft
- Subsequent aircraft
  - Take solutions of previous aircraft as constraints
- Implicit priority scheme
  - Earlier aircraft have an advantage

Algorithm overview

Algorithm 1 Decentralized MPC algorithm

Require: $\mathbf{q}_i(t), t = 0$ and $\mathbf{q}_{id}^F, \forall i \in \{1, \ldots, m\}$

```
while ∃i s.t. ‖q_i(t) − q_id^F‖_2 > Δ do
    Fix a priority for the aircraft
    for j = 1 to m do
        Solve problem (9) for aircraft j
        Broadcast q̄_jd to all aircraft
    end for
    Evolve the system according to (1) and (8) from t to t + T
    Set t = t + T
    Measure new aircraft position q_i(t)
end while
```

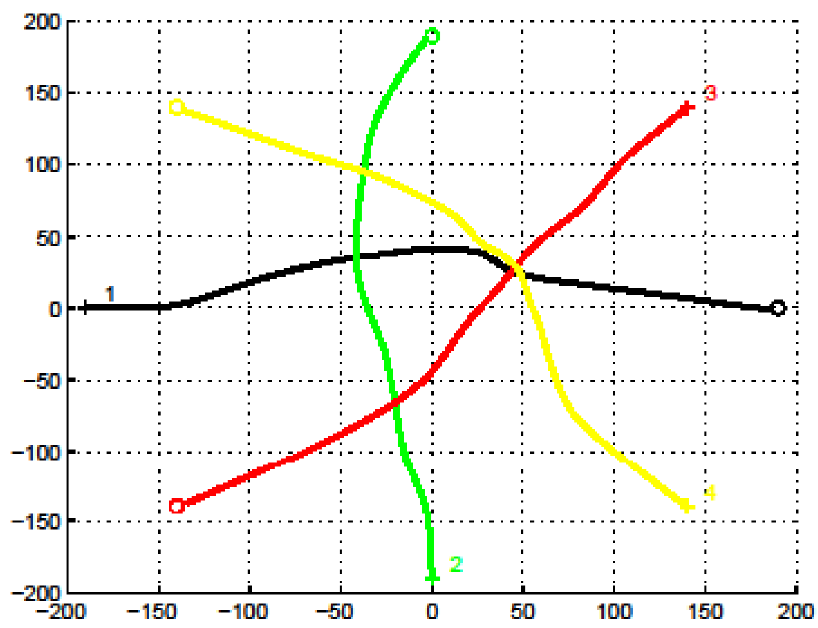
- **while** $\exists i$ s.t. $\|\mathbf{q}_i(t) - \mathbf{q}_{id}^F\|_2 > \Delta$ **do**
  - Fix a priority for the aircraft
  - **for** $j = 1$ to m **do**
    - Solve problem (9) for aircraft j
    - Broadcast $\bar{\mathbf{q}}_{jd}$ to all aircraft
  - **end for**
  - Evolve the system according to (1) and (8) from t to $t + T$
  - Set $t = t + T$
  - Measure new aircraft position $\mathbf{q}_i(t)$
- **end while**

Decentralized approach

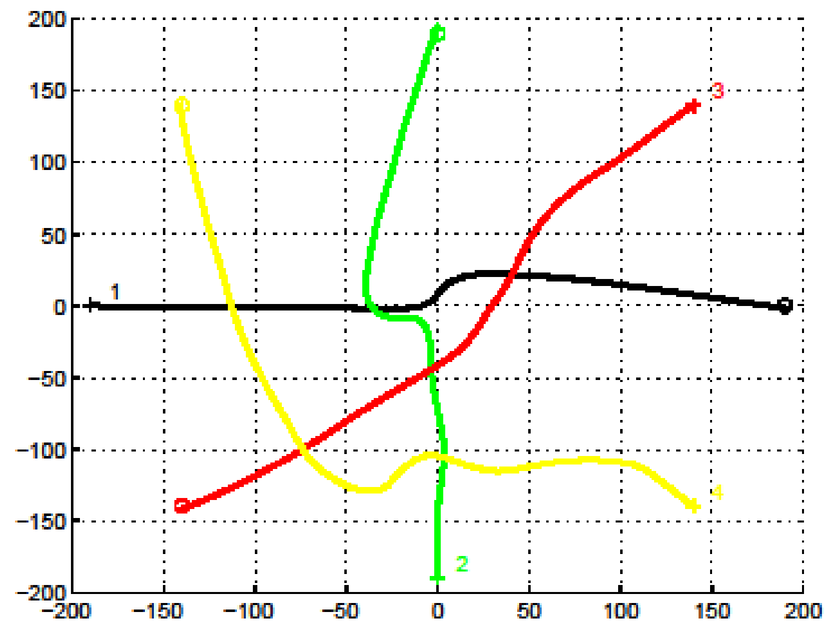
- Feasibility:
  - If centralized problem feasible so is decentralized
- No need for an initial centralized solution
- Previous round solutions can be used as “seed”
- Aircraft only need to communicate targets
- Every aircraft optimizes only its own cost
- No incentive to be a team player
- To be “fair”:
  - Introduce a fairness factor
  - Randomize optimization sequence at each step
  - Variable, soft priorities

Simulation Results

Centralized

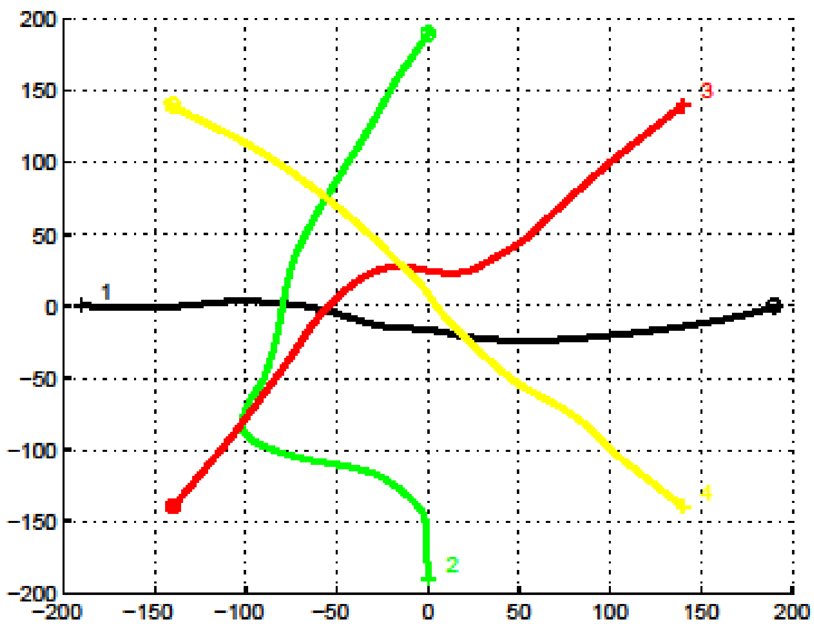


Decentralized (Round Robin)

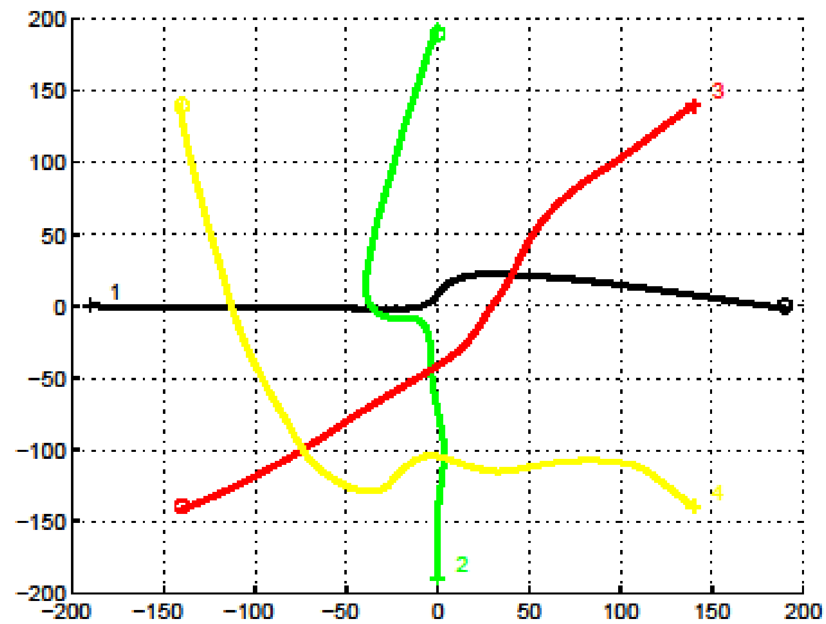


Simulation Results

Random order

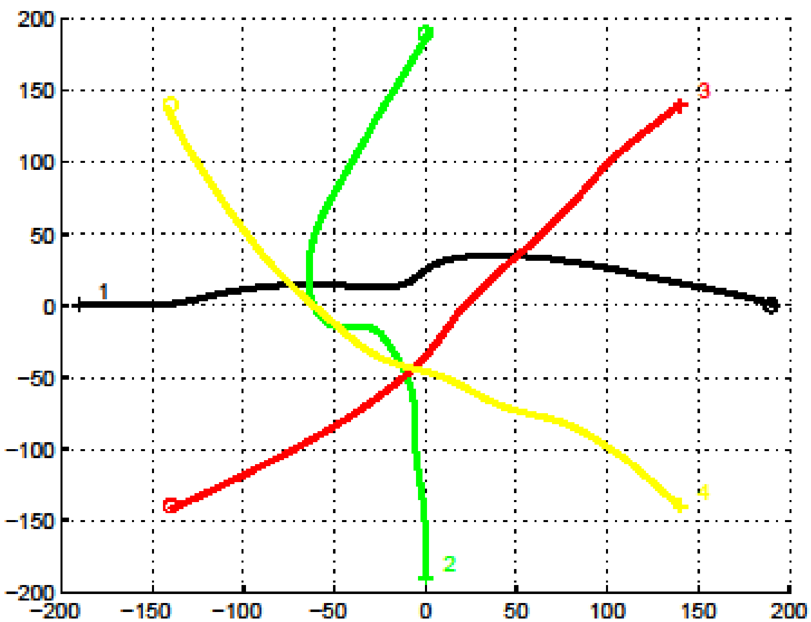


Round Robin

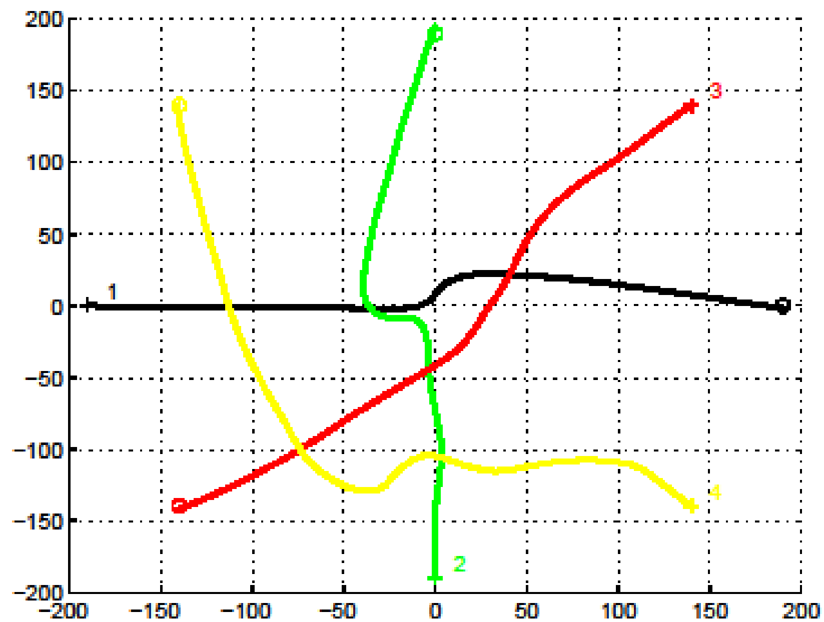


Simulation Results

Round Robin with additional cost



Round Robin



Simulation Results

- Round–robin implicitly define priority
- Implicit coordination of Navigation Functions limits benefit of being the first to optimize
- Effect can be further reduced by
  - Changing optimization order at each round
  - Introducing a "team player incentive"
- On the down side:
  - Optimization problem still hard
  - Addition of human factor considerations, maneuver alternatives, etc.
  - Proofs of performance very difficult

Summary

- A hierarchical control scheme for decentralized Mid to Short Term Conflict Resolution has been proposed

- The scheme combines the proven conflict avoidance of the Navigation Functions method with the constraint handling by the use of MPC, allowing to minimize a desired cost function

- The algorithm carries all the feasibility properties of the corresponding centralized scheme

Outlook

- Introducing the pilot in the hierarchy
- Tuning the cost function to produce simpler to implement maneuvers
- Extending the scheme in 3D
- Testing the algorithm against realistic flight plans

Thank you for your attention!