

WP3 – Multilayer Distributed Control and Model Management

WIDE End User Panel Meeting
June 2010



Workpackage at a glance

- **Model management**

- Consistent modeling
- Structure-respecting identification and order reduction
- Experiment design
- Subspace model ID for large-scale systems.

- **Distributed MPC and state estimation**

- Decentralized MPC
- Distributed price-coordinated MPC
- Distributed state estimation.

- **Higher-level real-time optimization**

- Dynamical real-time optimizers for plant-wide optimization: stability, performance and robustness
- Optimal re-configuration of a network of distributed MPC controllers
- Algorithms for distributed optimization of large-scale problems.

- **Prototyping and concept integration**

- Matlab toolbox with core algorithms
- Prototypes for DEMO
- Support for integration with other work-packages.

Model management



Model management

- **Objective:** modeling framework for large-scale hierarchical / distributed control and optimization
 - Models for control and optimization at different levels of decision/making
 - Different levels of fidelity (bandwidth, operational range) suitable for a particular purpose.
 - Consistent to each other
 - Uncertainty estimates to be available for robust control design
- **Issues:** model identification and order reduction in large-scale interconnected systems
 - Managing complexity
 - Exploiting *a priori* known structure
 - Designing identification experiments to obtain optimal models for a specific control purpose

Model merging 1

- **System ID of large-scale interconnected systems**

1. Identifying subsystems
2. Connect sub-models

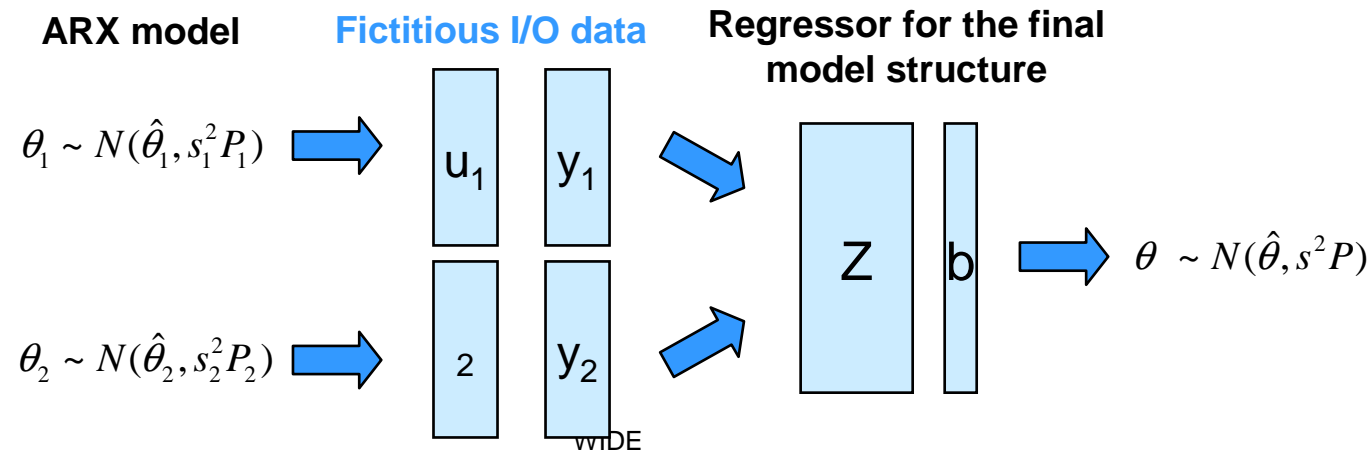
- **Challenges**

- Correct interconnections of sub-models (considering cross-correlations)
- Consistent handling of overlaps in identified models

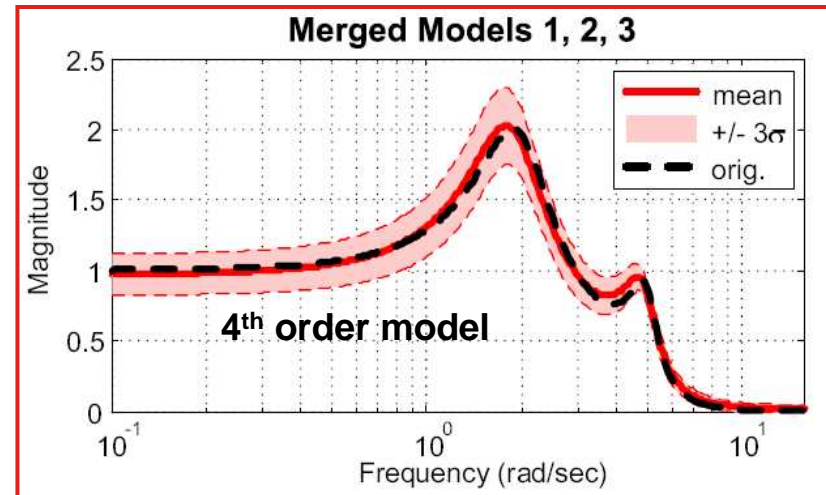
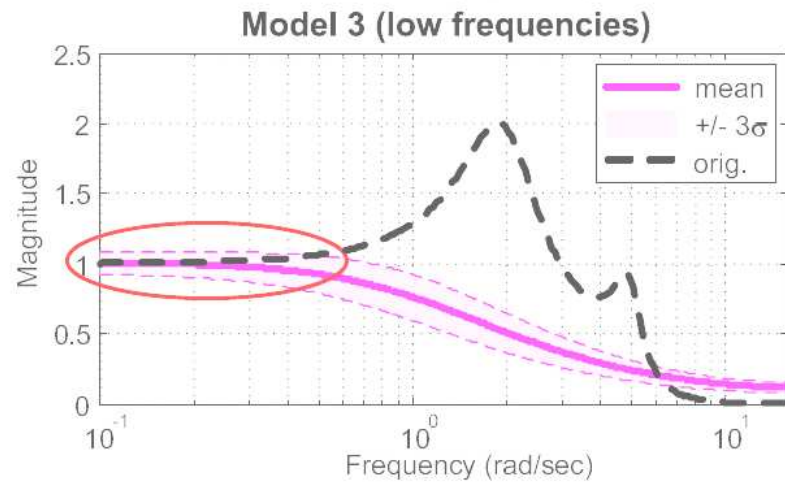
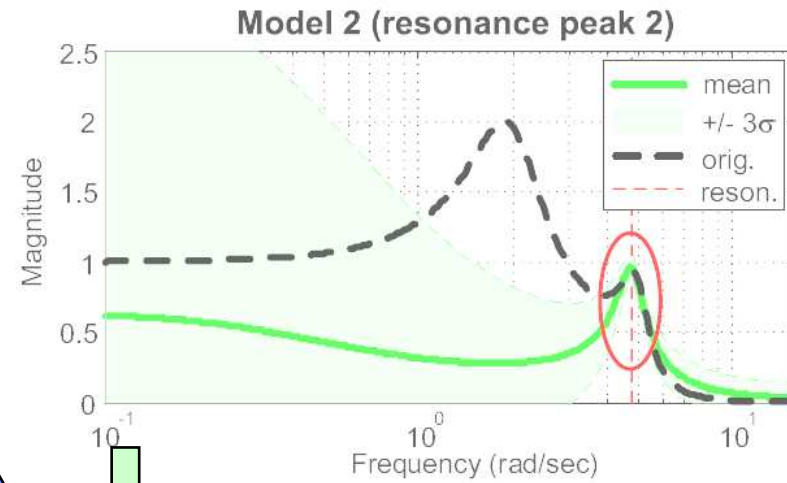
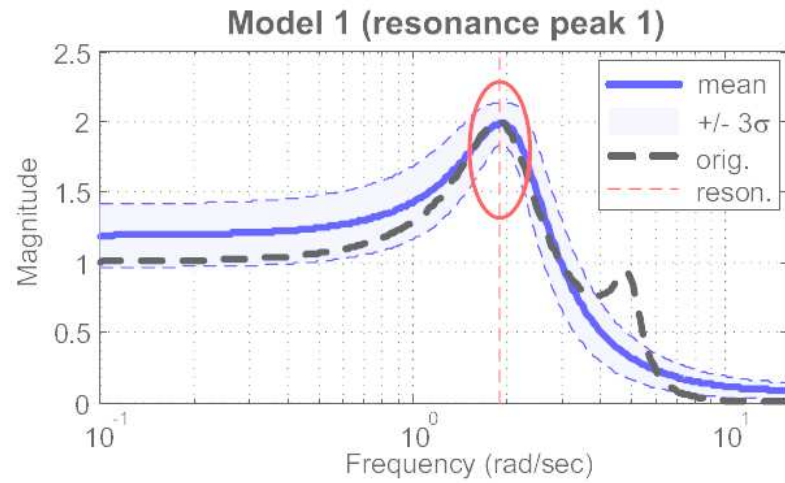
- **Merging ARX models of the same process**

- Different model orders
- Different spectra of the excitation signals – different quality of models
- Merging not possible in parameter space

- **A novel method was obtained based on fictitious I/O data**



Model merging 2



Structure-respecting modeling

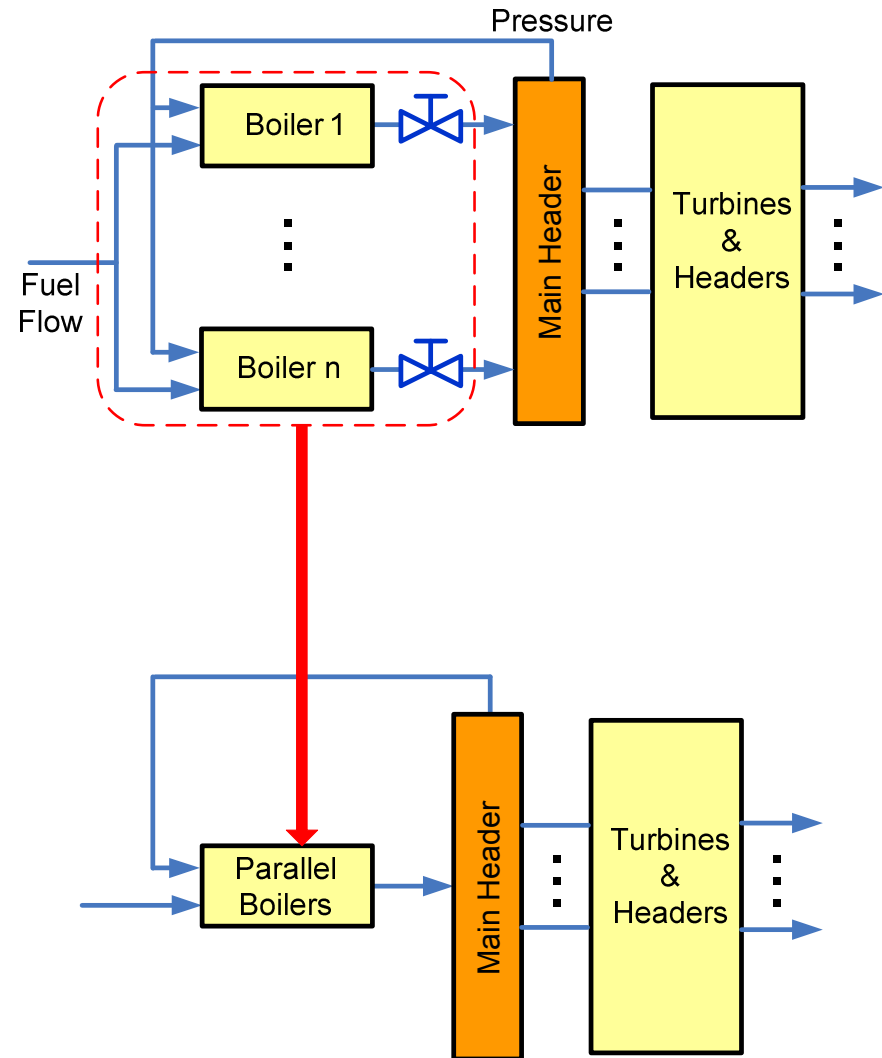
- **Structured order reduction**

- Goal: obtaining reduced-order model preserving interconnection structure
- Prior KTH result – order reduction of serial connection
- Extension in WIDE: order reduction for parallel systems.

- **Motivation**

- Units operating in parallel frequently occur in the industry (e.g. boilers feeding steam to a common header).
- Not all units operate simultaneously – combinatorial number of configurations of different control models
- A systematic procedure was proposed

- **Proposed solution outperforms non-structured reduction method and is comparable to a heuristics for boilers**



Distributed MPC and state estimation



Distributed MPC and state estimation

- **Objectives:**

- Developing novel methods for model-based predictive control for large-space systems
- State-estimation for output-feedback distributed MPC.

- **Approach**

- Distributing computational load among multiple units
- Different schemes of inter-unit communication
 - ◆ Decentralized
 - ◆ Cooperating
 - ◆ Coordinated

- **Issues**

- Handling complexity – limitations on computational resources
- Control issues – stability, robustness
- Communication issues – integration with WP4
- Flexibility – robustness to topological changes in controlled network.

Distributed MPC

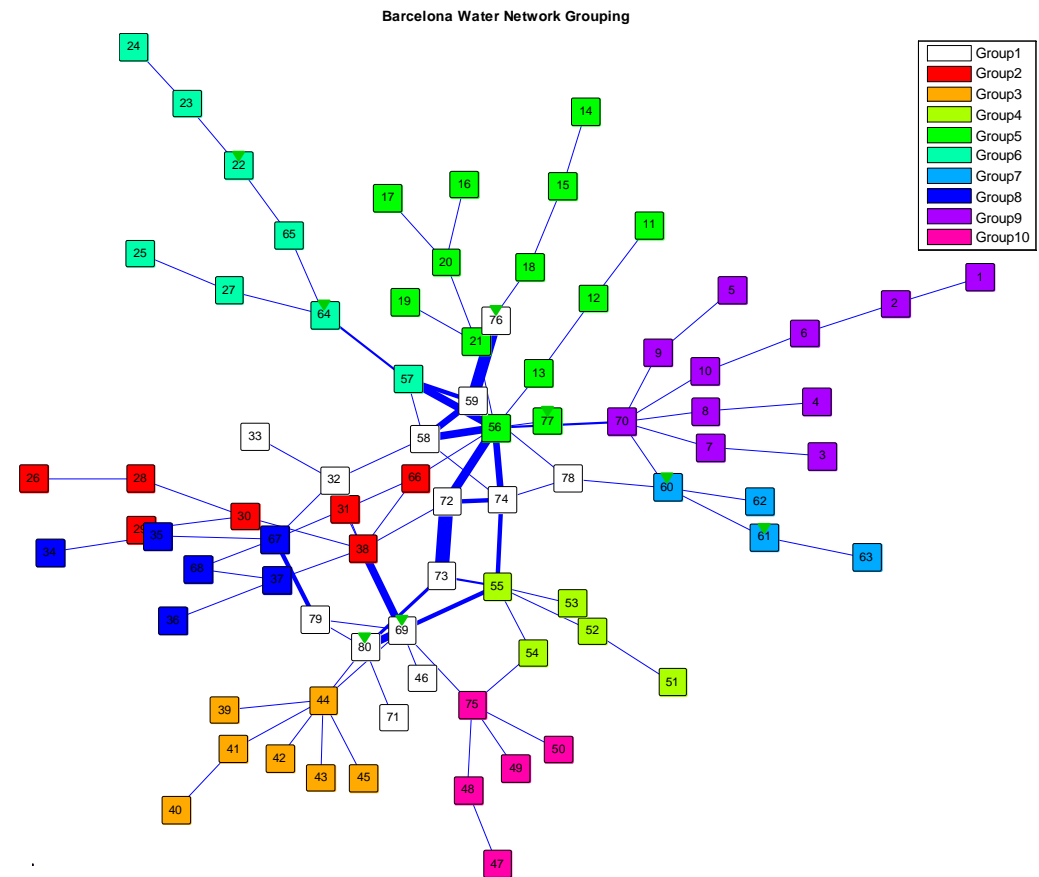
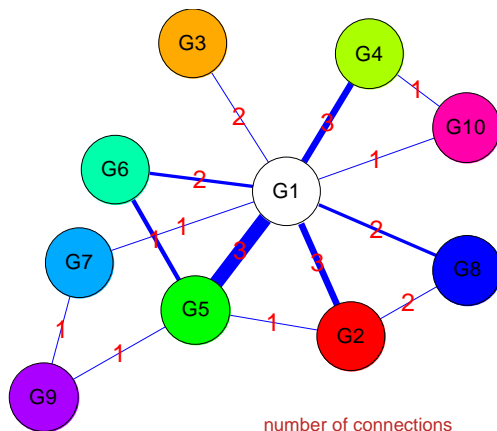
- **Decentralization based on Dual decomposition of Quadratic Programming:**
 - *Each controller solves its own local optimization problem.*
 - Each local optimization problem includes a term related to fulfillment of coupling constraints scaled by coordinate prices.
 - The **coordinator** manipulates prices in order to minimize the disagreement on coupling constraints.
 - Under convexity assumption, equilibrium prices are found that all coupling constraints are achieved and the **global optimum is reached**.
- **Iterative algorithm ($\sim 10^2$ iterations in 1 sampling period)**
 - Trading high computational load for large data exchange
 - **Suitable for slow processes as water networks**
- **Coordination algorithm**
 - **Centralized** (hierarchical architecture) – faster convergence
 - **Decentralized** (peer-to-peer communication) – slower but tolerant to topology changes

Distributed MPC – water network example

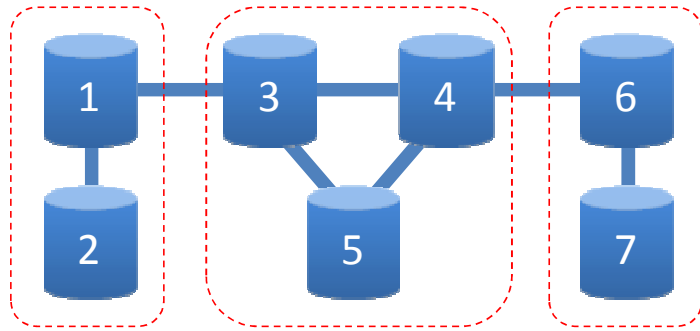
- **Network decomposition**

- **WN** → **graph** (edge weight ~ pumping capacity between tanks)
- **Step 1:** Condensation of leaves (condense all leaves with parents)
- **Step 2:** Epsilon decomposition of the remaining network

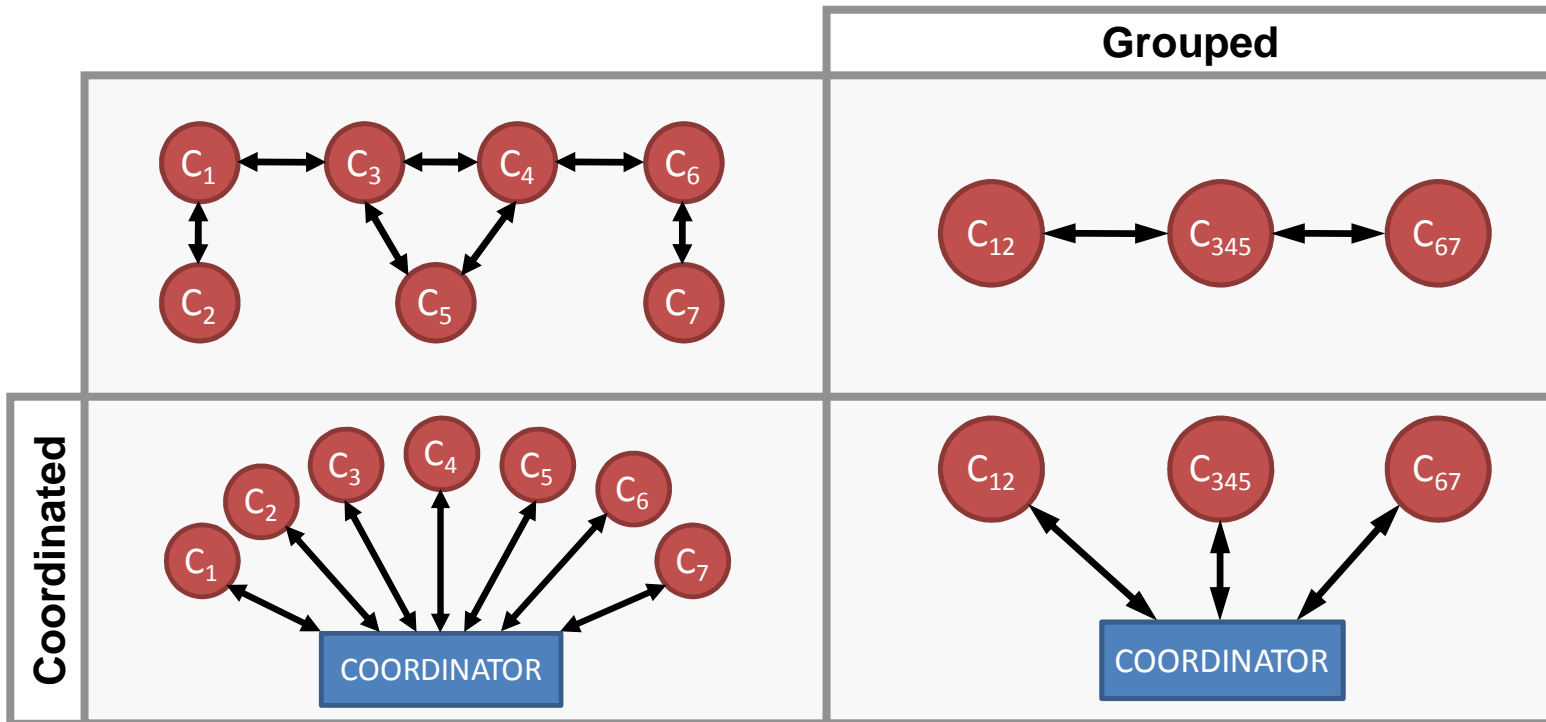
Aggregated Groups Interconnection



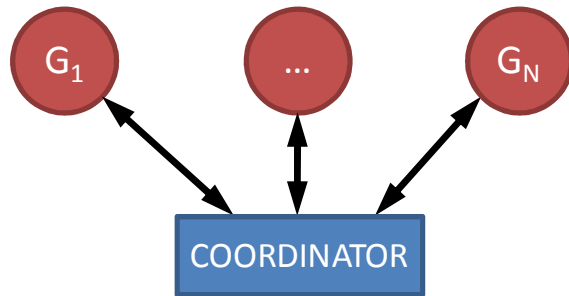
Architectures for distributed control



Centralized
Controller



Distributed MPC – central coordinator



- **19 subsystems**
- **Central coordinator**
 - Quasi-Newton L-BFGS
- **Stopping condition:**
 - worst consensus error < 1 m³/hrs

Sub-problem sizes:

Group 1:

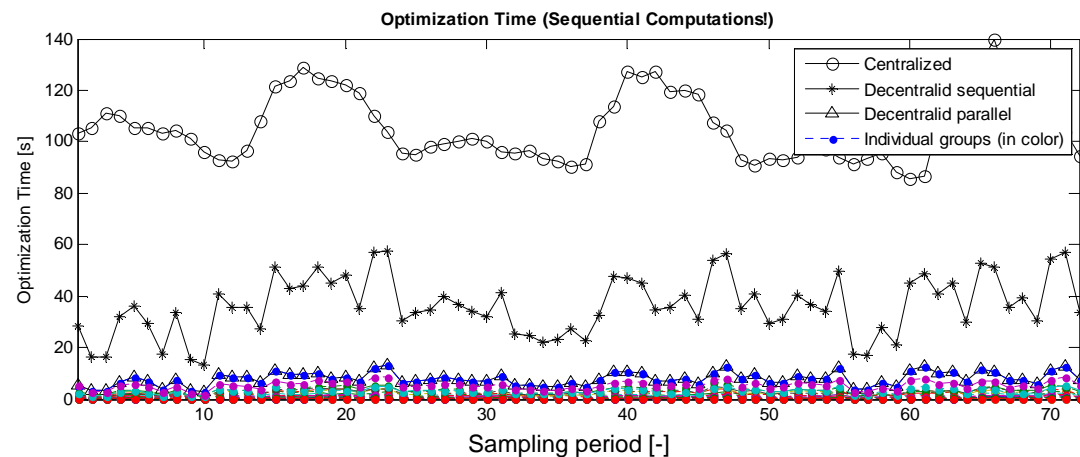
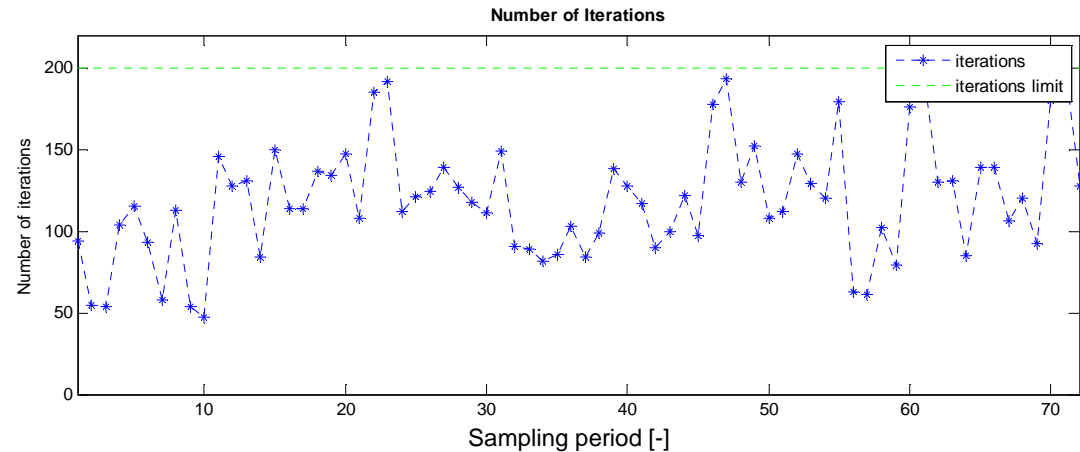
Number of variables = 220
 Non-equality constraints = 440

Group 2:

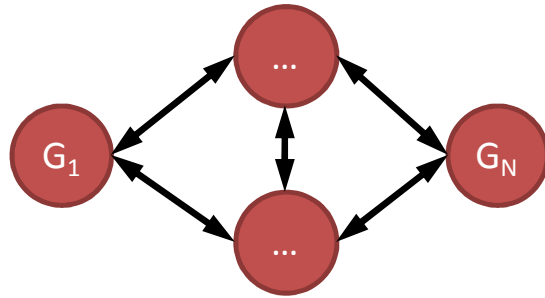
Number of variables = 140
 Non-equality constraints = 280

Group 3:

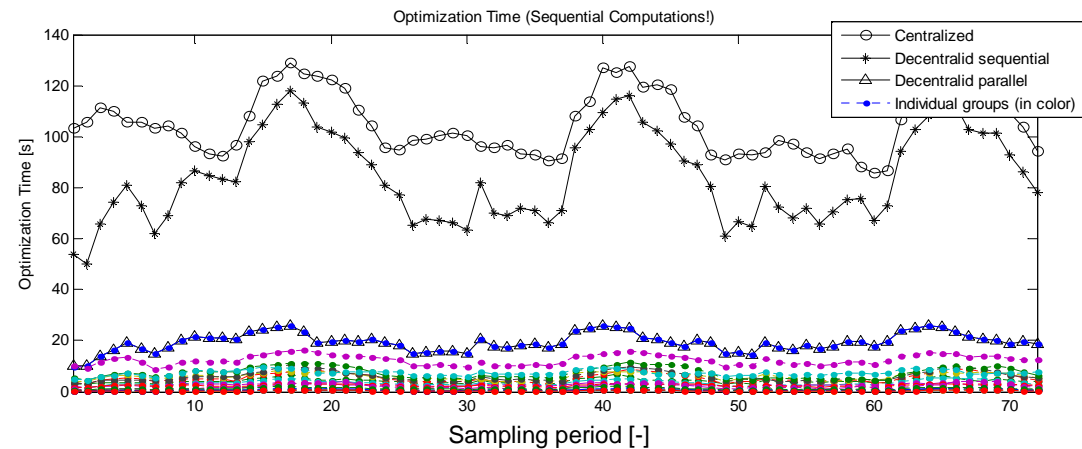
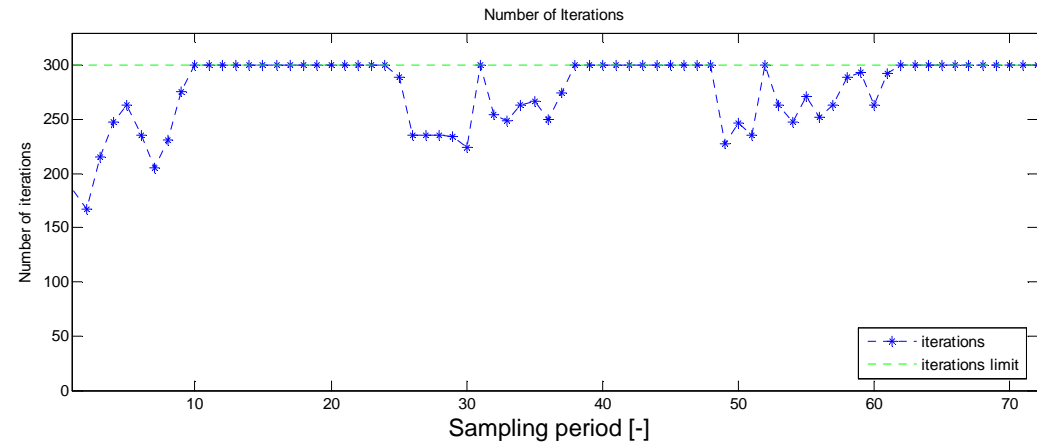
Number of variables = 150
 Non-equality constraints = 300



Distributed MPC – decentralized coordinator

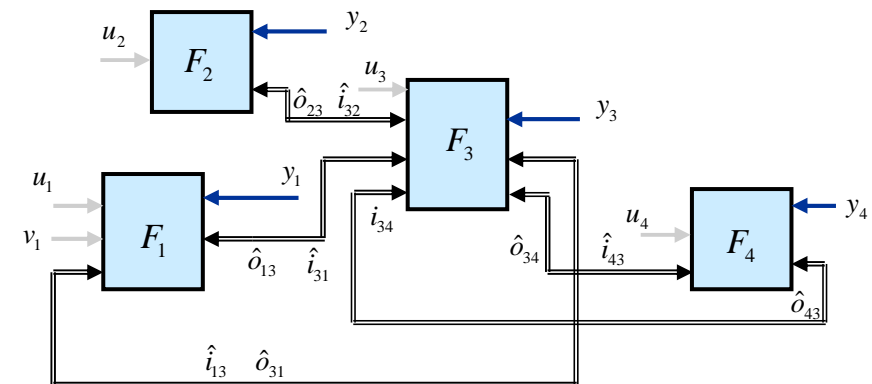
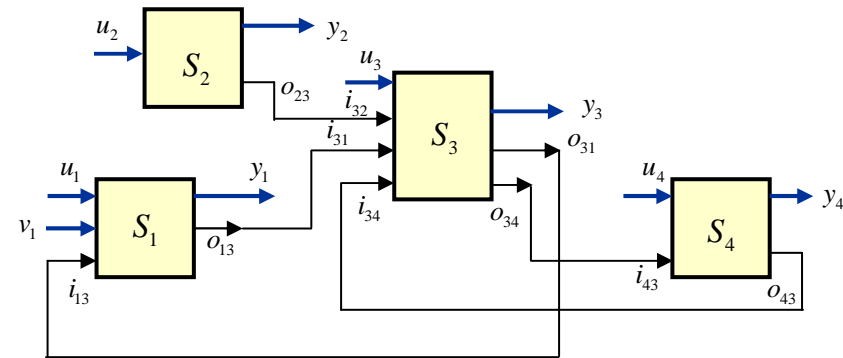


- **19 subsystems**
- **Local controllers communicate only with their neighbors**
- **Price coordination:**
Projected Nesterov gradient method



Distributed state estimation

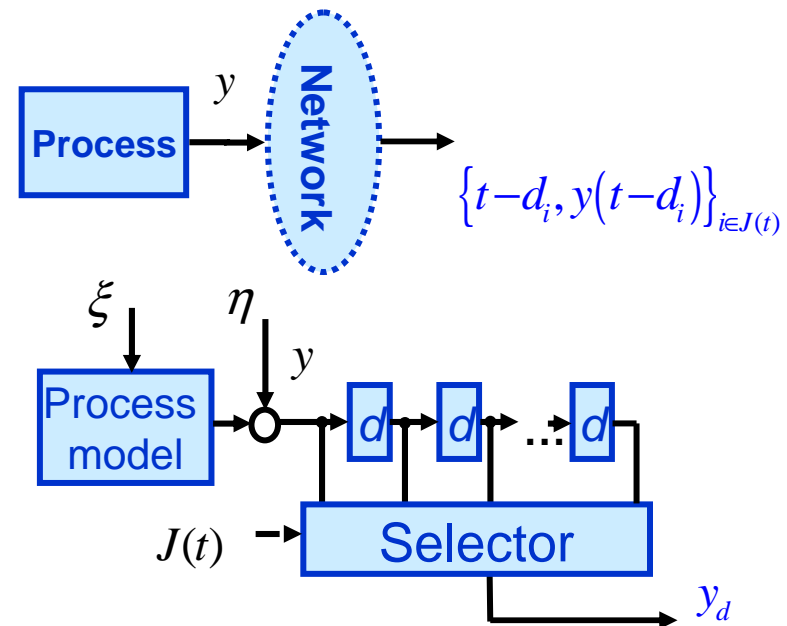
- **Motivation:** replacing state measurements in output-feedback distributed control.
- **Proposed solution:** Kalman filter network
 - topology corresponding to the process interconnection map.
 - Small overlap in locally estimated variables.
 - Local agents know only a part of the overall model
 - Generally sub-optimal (relative to the centralized Kalman filter).
 - Re-configurability, robustness to changes in network topology.



Kalman filter for systems with communication delays 1

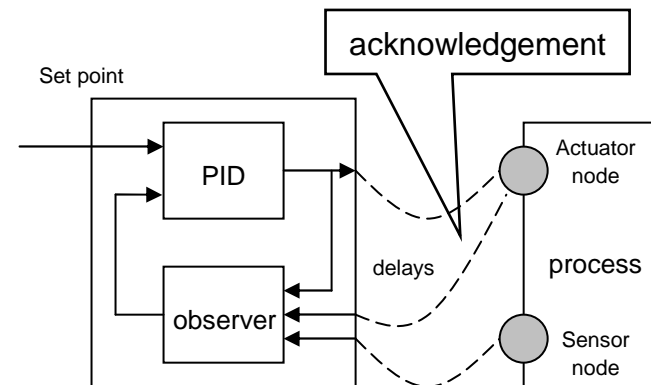
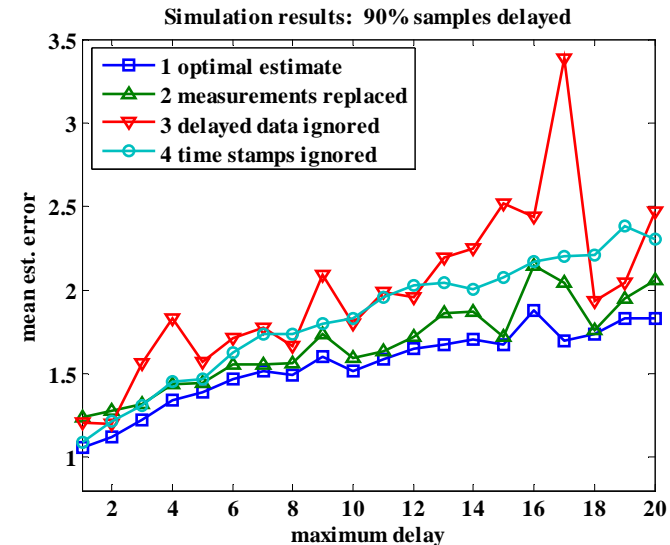
- **Process data transmitted over the network**
 - Delayed and lost packets.
- **Assumptions**
 - Delays in integer multiples of sampling intervals
 - Data transmitted with the time stamps.
- **Optimal estimator** – time varying Kalman filter for system augmented by a chain of delays
 - Finite length; longer delays \rightarrow lost data
 - Samples may arrive out of order, with several different time-stamps at a time.

- **New implementation of KF for this class of systems** – lower computational demand
 - A set of pre-computed gains
 - Recasting Riccati eqn into a dynamical equation of a reduced-rank matrix factor



Kalman filter for systems with communication delays 2

- **Time-varying Kalman filter**
 - computationally expensive for DCS
- Proposed **suboptimal solution**:
 - Missing values are replaced by estimates.
 - When the missing value arrives, the effect of value replacement is removed and the optimality recovered.
- A generalization:
 - Estimator is optimal when less than N samples is missing.
 - Pre-computed gains for each combination of missing samples
- On-line computational complexity
 - moderate increase relative to asymptotic KF



Higher-level RTO



Higher – level RTO

- **Objectives**

- *Framework for robust integrated plant-wide control and optimization*

- **Going beyond the classical steady-state economic optimizer paradigm.**

- Optimizer computes optimal set-points/steady state targets.
 - Subordinate MPC is responsible for achieving these targets.

- ***Dynamic optimizer*** is needed for better responsiveness to demands

- Transitions is costly and/or result in off-specs products
 - Significant delays, storages and recycle loops between units controlled by MPC.

- **Issues**

- Stability and robustness of the interlayer integration considering feedback spanning several layers.
 - Uncertainty handling in the hierarchical framework and worst case control.
 - Integrating a centralized hybrid MPC – optimizer (higher level) and decentralized linear MPC (lower level).