HPL overview

WIDE kick-off meeting

Siena

September 26-27, 2008

Honeywell

Outline

Honeywell

- About the partner
  - Honeywell
  - HPL team
- R&D in WIDE area
  - System identification
  - Decentralized optimization
  - Wireless control networks

Honeywell International

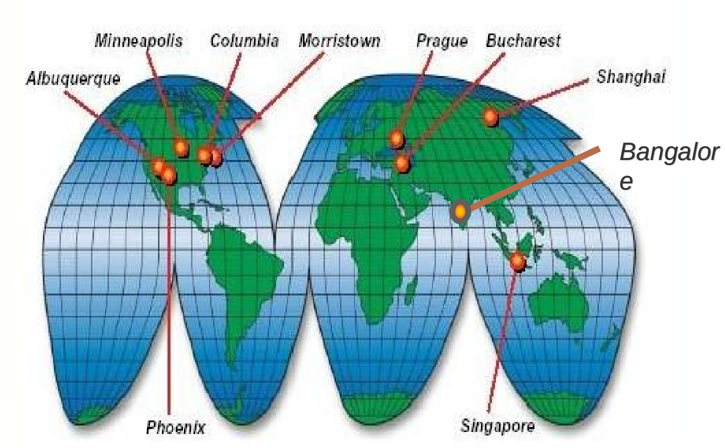
Honeywell

- 122,000 employees
- over 100 countries
- A *Fortune* 100 company – 2007 sales $34.6B
- 1000+ APC/RTO applications
  (Profit Suite, UES – developed in HPL)

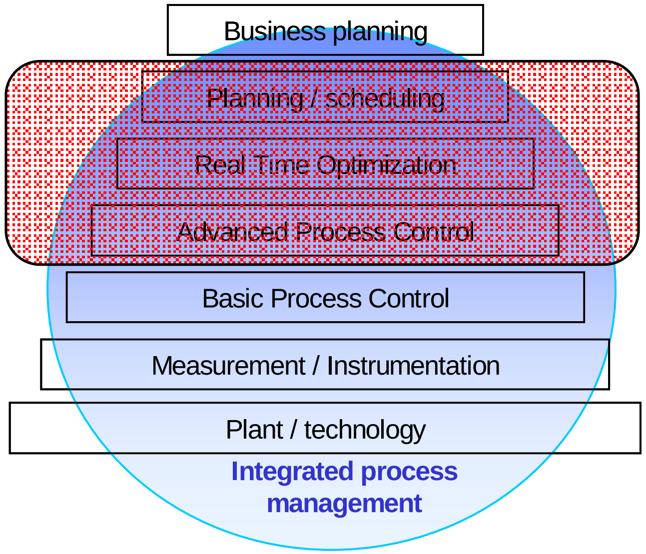
Honeywell's Research Organization

- $750M Spent Annually on R&D
- R&D supporting all business segments
  (ACS, AERO, SM, TS)
- ACS and AERO Labs
  - HQ'd in Minneapolis, MN
- Prague lab – branch of ACS AT lab
  - 30 employee, MSc/PhD level
  - PCO / DCT group
  - Control & optimization + domain knowledge
  - Algorithmic development → software prototyping → pilot testing
  - Productization / NPI (Bangalore)

Honeywell research organization



HPL PCO group scope



HPL alignment – ACS AT lab

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ACS Profile

$12.5B Revenue | **More than 55,000 Employees**

Process Solutions $1.8B	Building Solutions $1.9B	Sensing and Control $0.8B	ECC $2.1B	Security $1.8B	Life Safety $0.9B

Process Controls

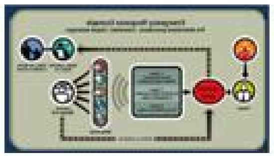
Distributed Control

EXPERION PKS Process Knowledge System

OneWireless

Buildings

Instant Alert

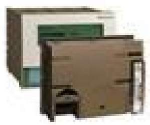


Speed and Position Sensors

Accelerometers

Pressure Sensors

Thermostats



Building Automation

Water Control

Gas Valves

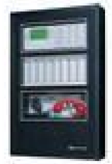
Motion / Human Presence Sensors

CCTV/ DVR User Interfaces

Control Systems

Fire/Smoke Sensors

System Panels



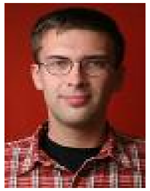
Home Medical Care

HPL WIDE related activities

HPL WIDE team








- Vladimir Havlena
  - MPC, bayesian/grey box ID
- Lubomír Baramov
  - Decentralized MPC / optimization / estimation
  - WP3 leader
- Daniel Pachner
  - Stochastic MPC, cautious optimization, NL identificaiton
- Jaroslav Pekař
  - MPC, modeling
- Pavel Trnka
  - Subspace identification, WCN (resource allocation)
- Jiří Findejs + sw developer team
  - SW development, prototyping
  - WP5 implementation support

R&D in WIDE area

Subspace identification method for MPC

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Subspace Identification for MPC

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Objective

- Subspace identification methods (SIM) tools for industrial applications of MPC, grey box modeling

Results

- SIM “formal algebraic methods without direct interpretation …” → interpretation of SIM as weighted multi-step predictor
- Elimination of causality problems and over-parameterization of standard algorithm
- Bayesian interpretation → incorporation of prior information to SIM

Causality and Over-parameterization issues

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Core SIM data equation

$$Y_f = \Gamma X_f + HU_f = \underbrace{LW_p}_{\text{Past data}} + \underbrace{HU_f}_{\text{Future inputs}}$$

$$H = \begin{bmatrix} h_0 & & & 0 \\ h_1 & h_0 & & \\ \ddots & \ddots & \ddots & \\ h_{i-1} & \ddots & \ddots & h_0 \end{bmatrix}$$

Enforcing *H* structure in estimation of *L* and *H* (S4ID – *H* full !!)

- formula for matrix product vectorization

$$vec(AB) = \left(B^T \otimes I\right) vec(A)$$

- unique *H* parameters $h_0, \ldots, h_i$

$$vec(H) = N \begin{bmatrix} h_0 \\ \vdots \\ h_{i-1} \end{bmatrix} \rightarrow vec(Y_f) = \underbrace{\left(\begin{bmatrix} W_p^T & U_f^T \end{bmatrix} \otimes I\right) \begin{bmatrix} I & 0 \\ 0 & N \end{bmatrix}}_{\text{Data Reorganization}} \begin{bmatrix} vec\, L \\ \hline h_0 \\ \vdots \\ h_{i-1} \end{bmatrix}$$

- *L* structure still to be enforced (rank + consistency with *H*)

SWLRA of block Hankel matrices

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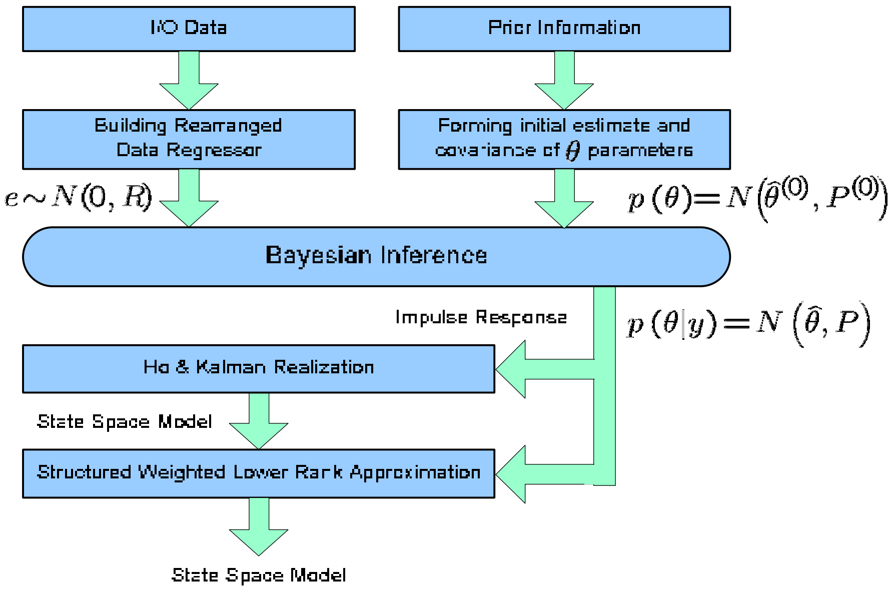
$$\mathrm{vec}\left(Y_f\right)=\left(\left(W_p^T \quad U_f^T\right)\otimes I_x\right)\begin{pmatrix} I_r & 0 \\ 0 & H \end{pmatrix}\begin{pmatrix} q_{kf} \\ q_h \end{pmatrix}=Zq$$



Optimal solution of realization problem

- Keep prior info in the realization step

$$\min_{A,B,C,D}\begin{pmatrix} h_0 - D \\ h_1 - CB \\ \vdots \\ h_{k-1} - CA^{k-2}B \end{pmatrix}^T P_h^{-1}\begin{pmatrix} h_0 - D \\ h_1 - CB \\ \vdots \\ h_{k-1} - CA^{k-2}B \end{pmatrix}$$

- Approach:

block Hankel matrix *H* of rank *n* equivalent to s. s. model of n-th order

$$H = \Gamma_i \Delta_i, \qquad \Gamma_i = \begin{pmatrix} C \\ CA \\ \vdots \\ CA^{i-1} \end{pmatrix}, \qquad \Delta_i = \left(B \quad AB \quad \cdots \quad A^{i-1}B\right).$$

- Solution = SWLRA
  - for scalar Hankel matrices solution exists
  - solution for MISO – algorithm published (does not converge)
  - solution for MIMO – new results

SIM Incorporating Prior Information

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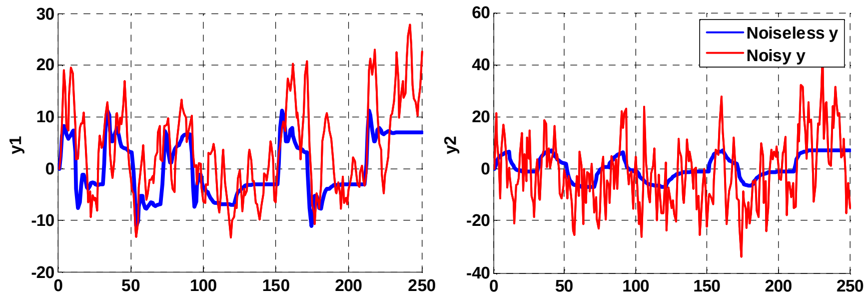
- 2 inputs / 2 outputs system of 5th order
- Additive **colored noise**

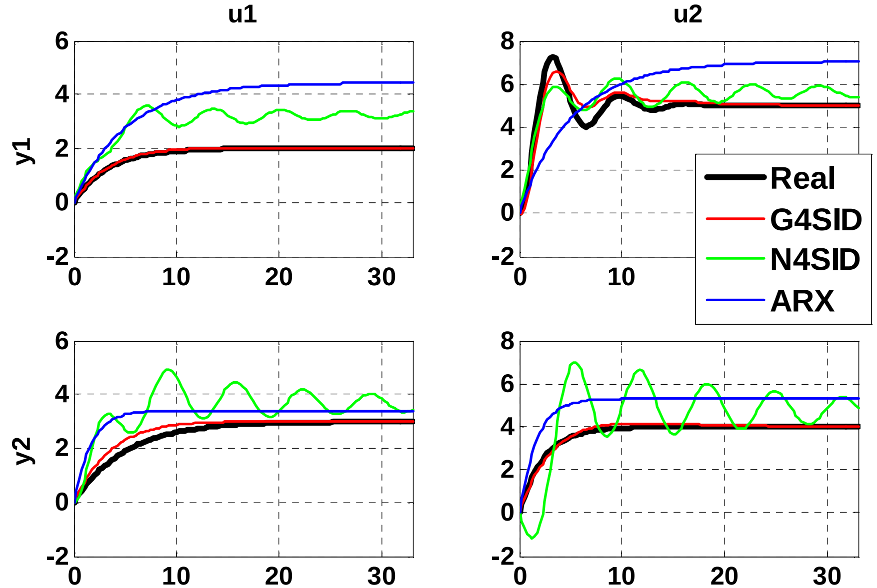
  (multistep predictor equivalent to repeated single-step predictions ?)



Fit Factor to Noiseless Measurements			
	Greybox 4SID	85%	91%
	Standard 4SID	71%	39%
	ARX	38%	63%

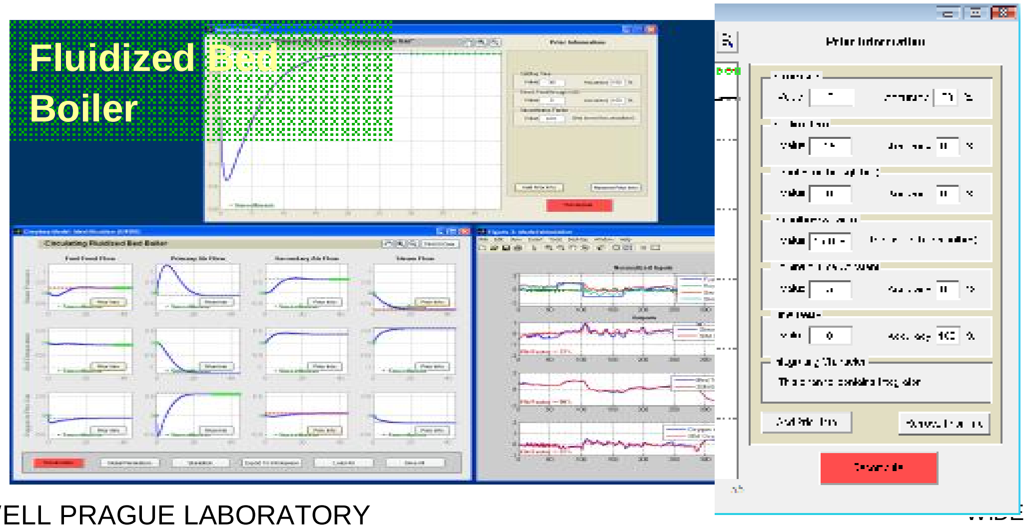
Estimated Step Responses

Prior information: static gains, frequency limits



Problem with industrial applications of APC/RTO = PEOPLE

- MATLAB tool
- Template solution concept
  - Fixed structure (MV, DV, CV)
  - Fixed prior info
  - Parameterized by data



Decentralized Steam Plant Optimization

Price Coordination Method

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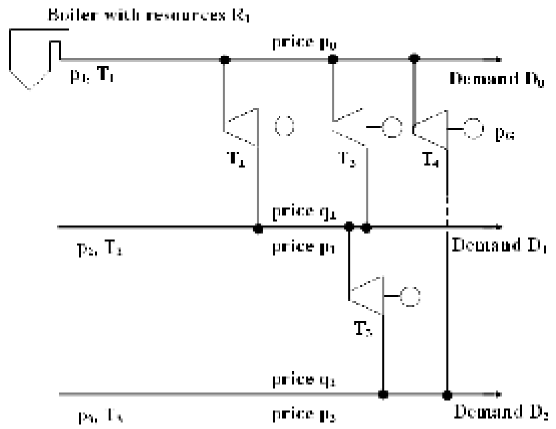
- **Two-level iterative scheme**
  - **Decomposition – set of interconnected blocks**
  - **Prices assigned to interconnected inputs and outputs**
  - **Primary task**

$$\hat{\mathbf{x}} = \arg\max_{\mathbf{x}} L^{pc} = \arg\max_{\mathbf{x}} \sum_{i=1}^{N} Q_i(\mathbf{x}_i) - <\boldsymbol{\lambda}_i^T, \mathbf{x}_i^i> + <\boldsymbol{\mu}_i^T, \mathbf{y}_i>$$

$$m_i = \sum_{j=1}^{N} h_{ji} l_j,\ y_i = f(\mathbf{x}_i)$$

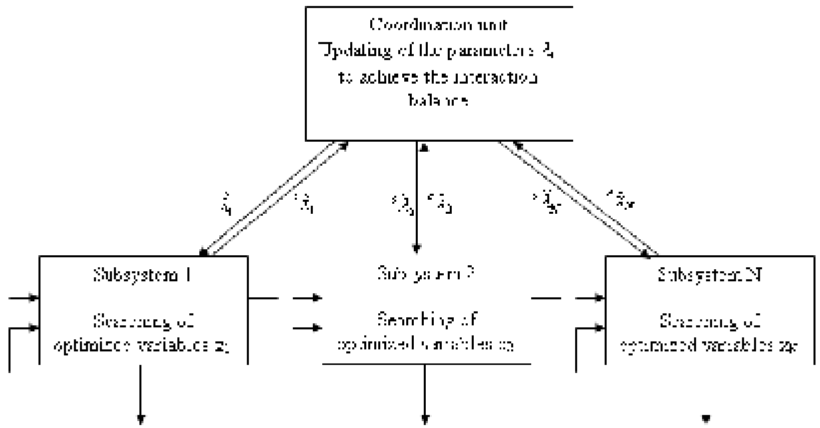


  - **Dual task (coordinator level)**

$$\hat{\boldsymbol{\lambda}} = \arg\left\{\min_{\boldsymbol{\lambda}}\left\{\max_{\mathbf{x}} L^{pc}(\boldsymbol{\lambda}, \mathbf{x})\right\}\right\}$$

    - update of prices $\boldsymbol{\lambda}$ to ensure balance

$$\mathbf{d} = \hat{\mathbf{x}}(\hat{\boldsymbol{\lambda}}) - \mathbf{B}\hat{\mathbf{y}}(\hat{\boldsymbol{\lambda}}) = 0$$



- **Solution of dual task**
  - **steepest descent**
  - **Newton method**
    - Hessian evaluated numerically in each iteration
    - singular Hessian → to be solved … ; method fast but unreliable
  - **modern mp-QP insight (for QP primary task)**
    - Hessian changes during localization of optimum (a set of polytopes)

Explicit Solution of Price coordination method

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- **Eliminate the disadvantages of Newton method (Hessian singularity, step length)**

- **Explicit solution of primary task**
  - **mp-QP optimization problem (primary task)**

$$\max_{\mathbf{x_k}} \mathbf{x_k}^T \mathbf{S_k} \mathbf{x_k} + \boldsymbol{\lambda}_\mathbf{k}^T \mathbf{M_k} \mathbf{x_k} + \mathbf{p}_\mathbf{k}^T \mathbf{x_k} + q_k \qquad \mathbf{A_k} \mathbf{x_k} \le \mathbf{b_k}, \quad k = 1, \dots, N$$

  - **solution in form of a PWA function of λ_k (for each subsystem)**

$$\hat{\mathbf{x}}_\mathbf{k}(\boldsymbol{\lambda}) = \mathbf{K}_\mathbf{k}^\mathbf{j} \boldsymbol{\lambda} + \mathbf{l}_\mathbf{k}^\mathbf{j}, \ j = 1, \dots, m$$

    - valid in polytope P_j described by

$$\mathbf{G}_\mathbf{k}^\mathbf{j} \boldsymbol{\lambda} \le \mathbf{h}_\mathbf{k}^\mathbf{j}$$

    - polytopes of different dimensions (depends on dim(λ_k))

Method Based on mp-QP

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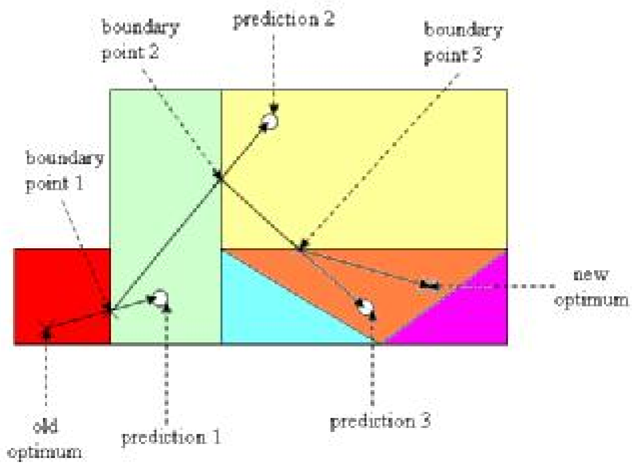
- partitioning of λ – space into set of polytopes
  - each polytope with singular or regular Hessian
- dual task: minimization of discoordination
  - transitions from one polytope to another
  - using "correct" Hessian (K_{BAL}) valid in particular polytope
- advantages of algorithm
  - no overshoots
  - fast convergence
  - Hessian known before optimization

$$\mathbf{d} = \hat{\mathbf{x}}(\hat{\boldsymbol{\lambda}}) - \mathbf{B}\hat{\mathbf{y}}({}^{o}\hat{\boldsymbol{\lambda}})$$

$$\mathbf{d} = \mathbf{K}_{\mathrm{BAL}}\hat{\boldsymbol{\lambda}}$$



Method Based on mp-QP

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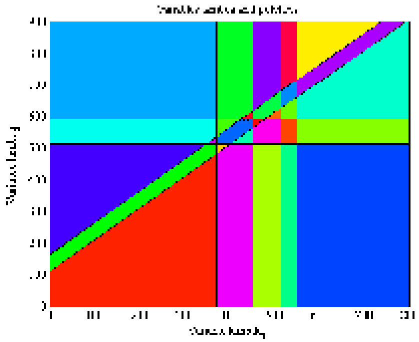
- **singular Hessian problem**
  - **detailed analysis of polytopes in λ–space and D–space**
  - **optimum is always located in polytopes with regular Hessian**
  - **only polytopes with rank(H) ≥ *n*-1 need to be traversed**

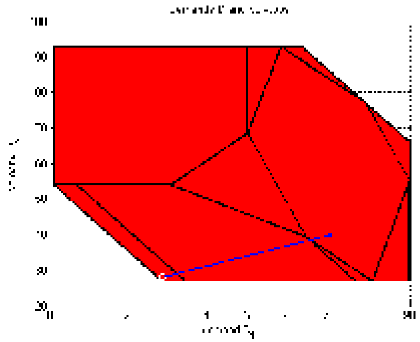
$$\mathbf{d} = \hat{\mathbf{x}}(\hat{\boldsymbol{\lambda}}) - \mathbf{H}\hat{\mathbf{y}}(\hat{\boldsymbol{\lambda}})$$

$$\mathbf{d} = \mathbf{K}_{\mathrm{BAL}}\hat{\boldsymbol{\lambda}}$$

,

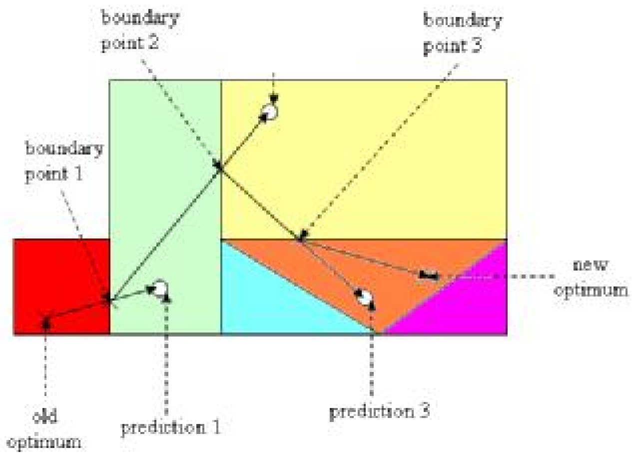
- rank K_{BAL}= n, n-1, n-2, ….





- **For singular H**
  - no discoordination change on polytope boundary in D-space
  - direction in λ–space given

$$\mathbf{K}_{\mathrm{BAL}}\hat{\boldsymbol{\lambda}} = 0$$



Example: comparison of the methods

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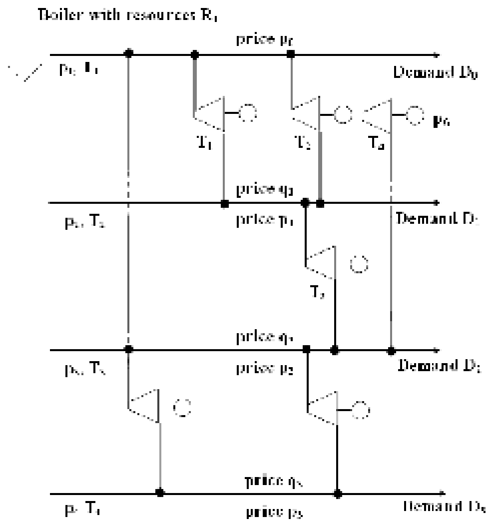
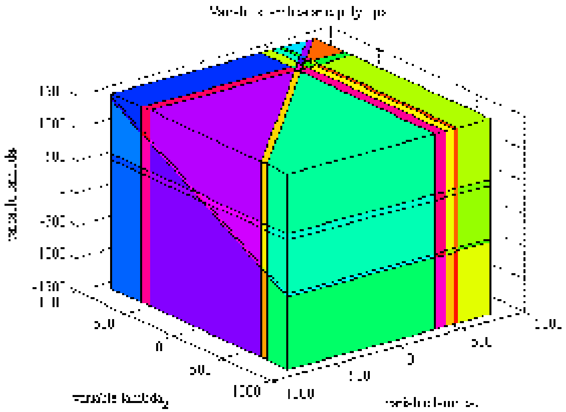
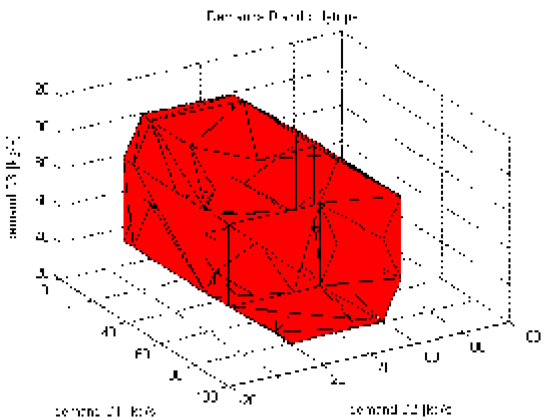
- **Max generation, given demand from individual headers**
  - **three headers**
  - **six backpressure/extraction turbines**







Steam demand changes / number of iterations		Steepest	Newton's method [-]				Proposed
Starting demand: D0 = [70;40;50] (kg/s)		descent [-]	Iteration	Subiterations	Sing. Hessian it.	Sum	method [-]
Demand D1:	[70 50 50]	77	2	36	0	38	2
Demand D2:	[40 60 30]	31	5	90	0	95	4
Demand D3:	[25 70 50]	109	3	54	67	124	3
Demand D4:	[45 49 85]	128	3	54	52	109	3
Demand D5:	[10 60 75]	95	3	54	48	105	3
Demand D6:	[40 70 30]	151	3	54	66	123	3
Demand D7:	[10 60 75]	97	4	72	66	142	3
Demand D8:	[30 20 95]	26	3	54	48	105	3
Demand D9:	[42 48 48]	92	3	54	48	105	3
Demand D10:	[40 60 30]	27	1	18	0	19	1

Wireless control networks

- optimal node allocation
- communication issues

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Optimal Resources Allocation in Wireless NCS

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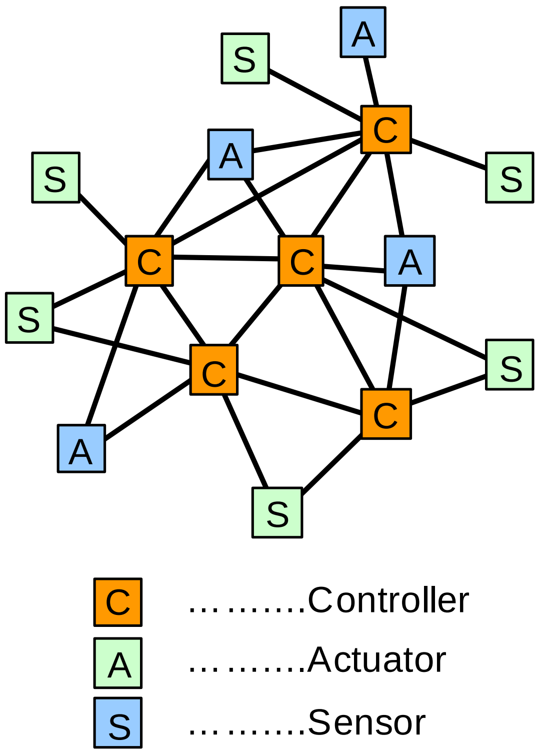
Optimization problem involving distribution of control algorithms to a set of controllers in networked control system. Each algorithm has certain computational load, needs to communicate with a set of sensors and/or controllers and has to be executed in certain number of instances.

Constraints:

- Computational power of controllers
- Links bandwidth
- Links quality

Considered Optimality:

- Minimization of hops between controllers and needed sensors and/or actuators
- Preference of high quality links
- Even distribution of CPU load
- Even distribution of communication traffic
- Robustness to link failure (without reallocation)
- Exclusion of links with quality bellow threshold



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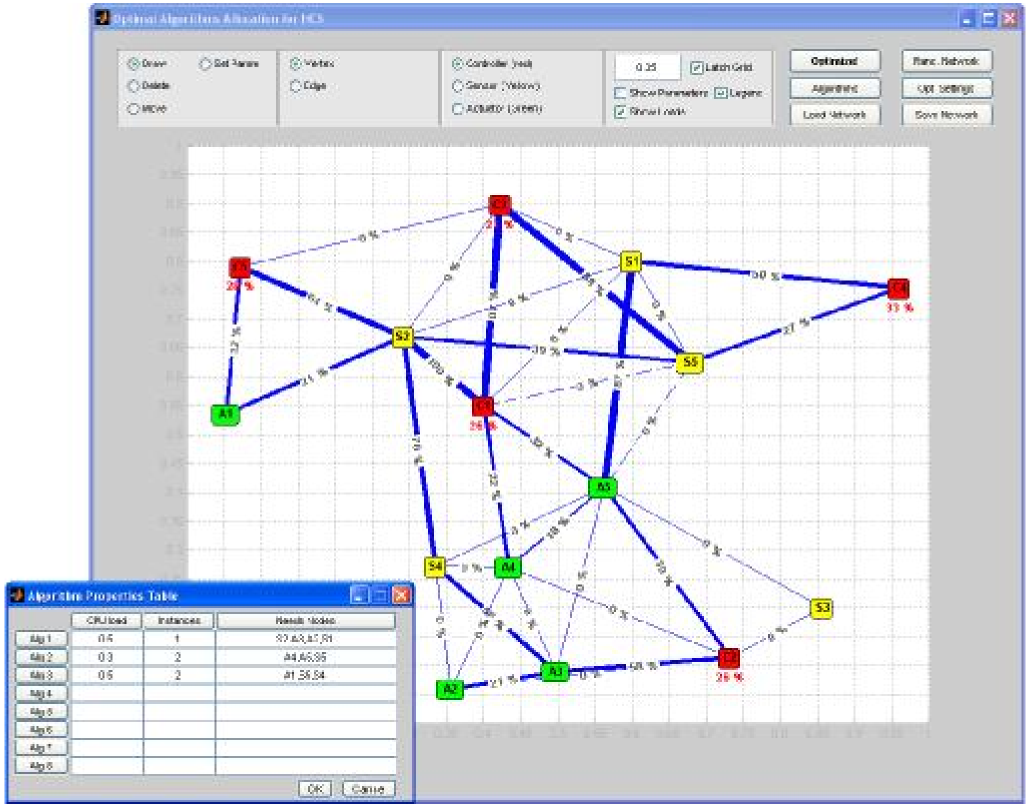
Algorithm

- Allocation algorithm was developed based on linear/quadratic binary programming.
- It allows to incorporate all optimization criterions mentioned on previous slide while complying with resources constraints.

- Algorithm can be used for networks with up to several 10's of nodes -> it can be used as a reference solution for suboptimal algorithms able to cope with larger networks.
- Algorithm optimally allocates algorithms to controllers and also finds best communication paths.
- Issue: scalability



Optimal Resources Allocation in Wireless NCS

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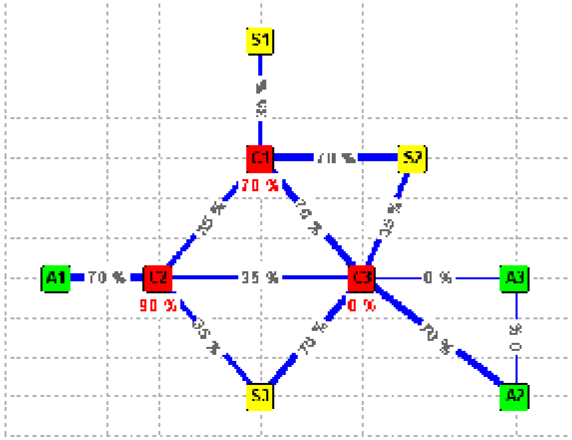
Small Scale Example

- 3 controllers, 3 sensors and 2 actuators
- Unit links bandwidths
- Unit controllers computing power
- Same links load for all algorithms = 35%

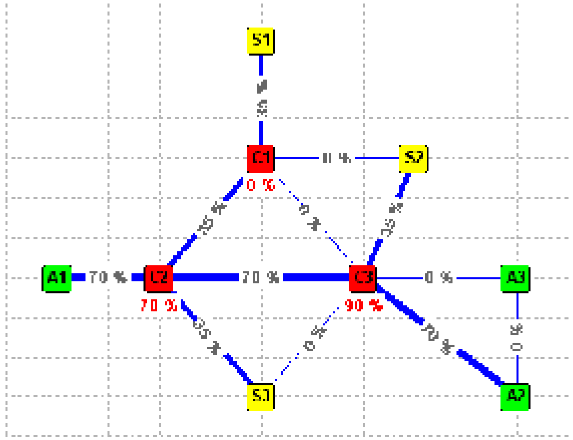
Alg.	Cont. load	Needs nodes
A1	50 %	S2,A2
A2	30 %	S1,S3,A2
A3	40 %	S3,A1
A4	40 %	S2,A1,A2

Feasible solution



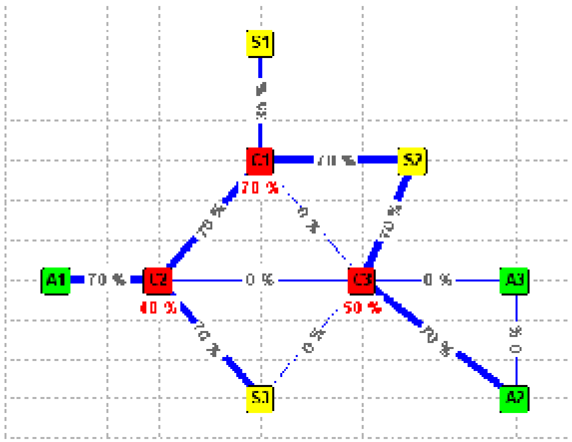
C1:(A2,A3), C2:(A1), C3:(A4)

Hops minimization



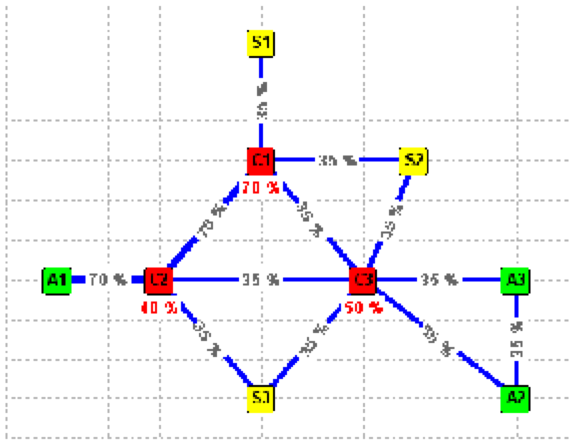
C1:(-), C2:(A3,A4), C3:(A1,A2)

Hops minimization & controllers load equalization



C1:(A2,A4), C2:(A4), C3:(A1)

Hops minimization & controllers and links load equalization



C1:(A2,A4), C2:(A4), C3:(A1)
(different routing to previous solution)

Compensation of communication delay

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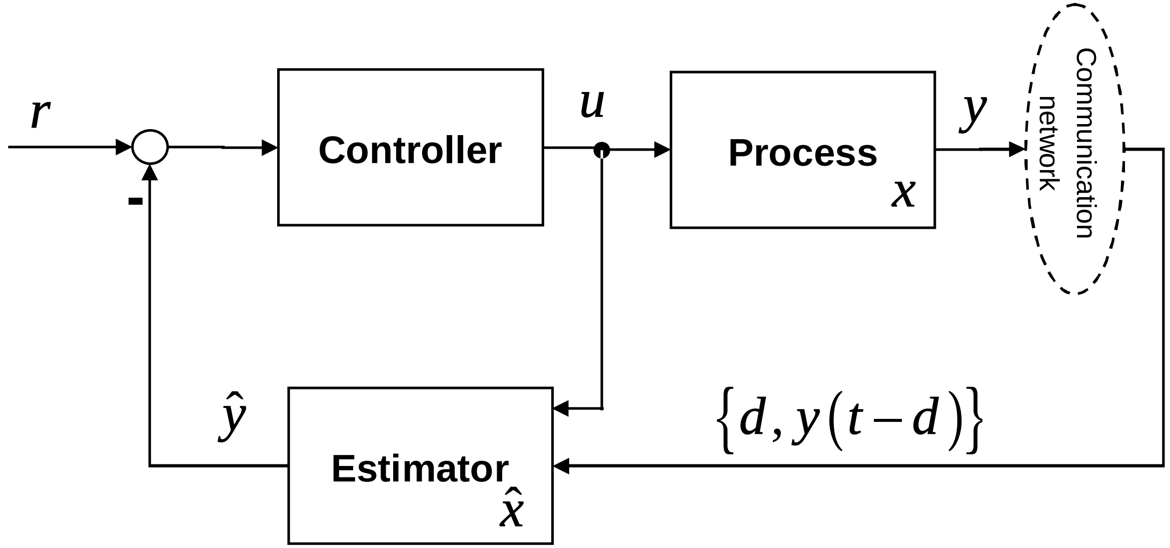
- **Using state estimator of augmented system for estimating current process output (SISO, MISO)**
  - Kalman filter replacing Smith predictor
  - added noise-cancelling and disturbance estimation capability

- **Several levels of complexity**
  - Optimal KF, multiple data at a time
  - Suboptimal KF, handling only the latest measurement
  - **Approximated by a switched gain** (set of pre-computed gains in a look-up table)
  - 1st/2nd order apporximations



- **Solution – dynamically augmented KF**
  - **tracking of missing samples**
  - **Bayesian insertion at “time of arrival” vs. Riccati formulation**
- **Easy to verify**
  - **DA KF with randomly delayed data**
  - **Standard Kalman filter (no delays)**
  - **States of both filters equal whenever all data available**
- **Suboptimal solution**
  - **Kalman gains calculated offline, gains stored in a look-up table**
  - **Direct analog of the time invariant Kalman filter**
  - **No second order statistics (covariance) need to be calculated**
  - **Scalable complexity – implemented as part of PID controller**
- **Out-of-sequence MVs**
  - **Dual problem**