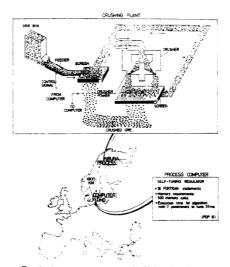
Lecture 13:: Applications

Early example of networked control

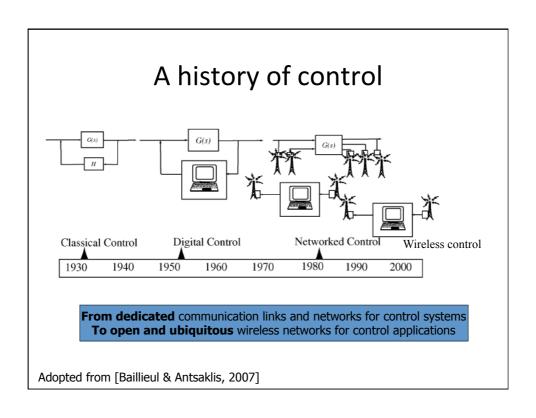
- Adaptive control of an Orecrusher in Kiruna (northern Sweden) in 1973
- Control computer located in Lund (southern Sweden) 1800 km away
- Sensor data and control commands were sent over the public telephone net with sampling interval of 20 s

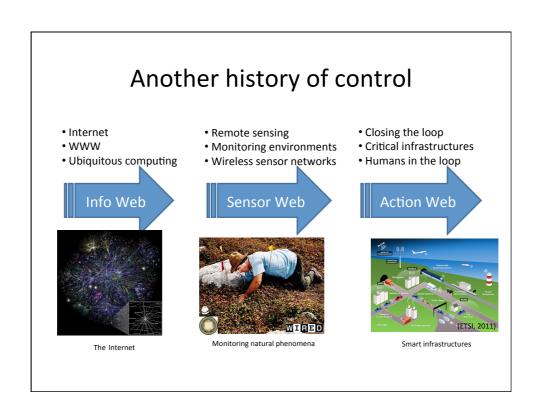


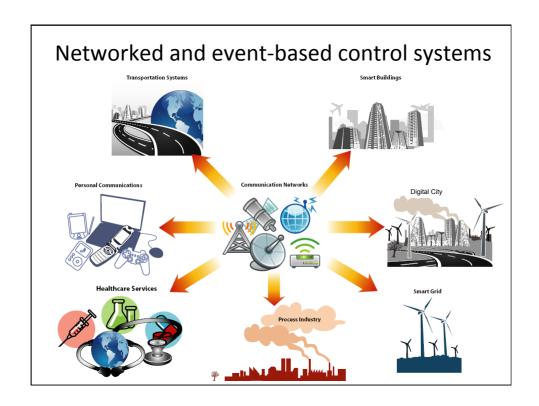
Borisson and Syding, Automatica, 11, 1975

Fig. 1. A process computer at the University of Lund

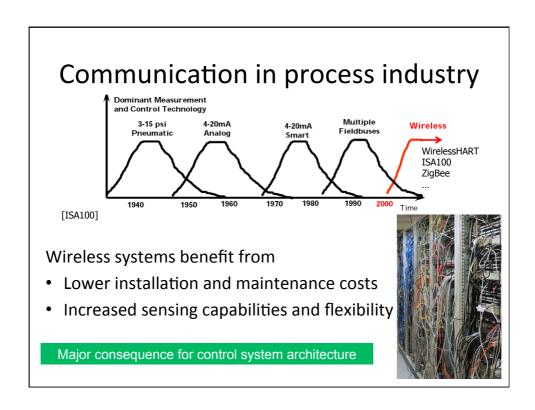
Karl H. Johansson, Wireles Connected to the crushing plant in Kiruna at 1800 km distance in a direct digital control loop.

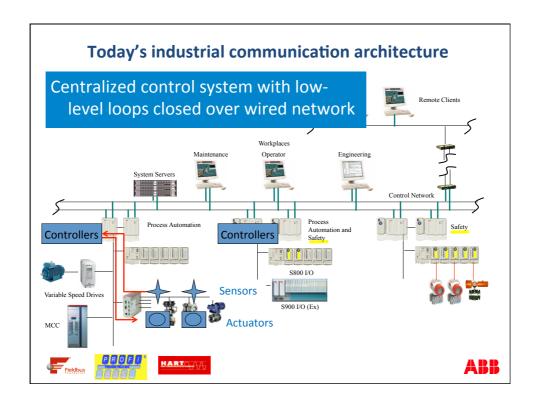






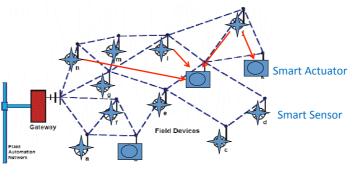
- Process industry
- Transportation systems
- Smart buildings

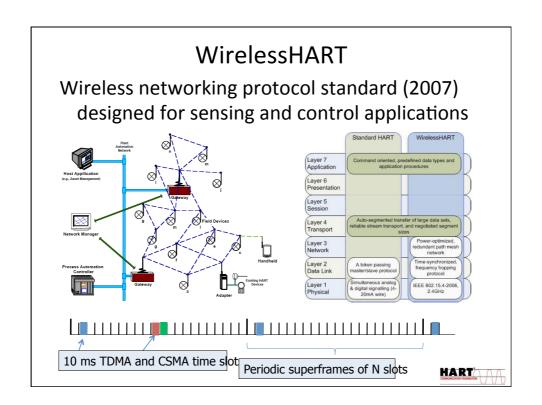


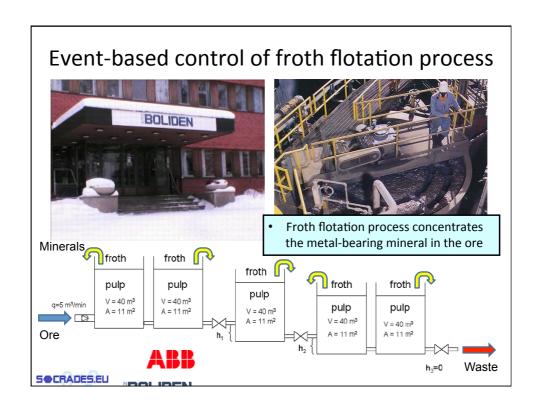


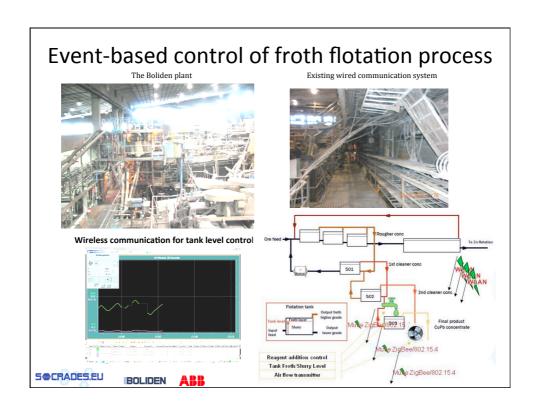
Towards wireless sensor and actuator network architecture

- Local control loops closed over wireless multi-hop network
- Potential for a dramatic change:
 - From fixed hierarchical centralized system to flexible distributed
 - From few dedicated computers to many smart sensors/actuators





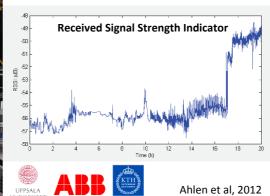




Radio Channel Measurements in Industrial Environment



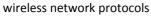
- Rolling mill at Sandvik in Sweden
- Study of 2.45 GHz radio channel properties
- Slow but substantial RSSI variations due to mobile machines



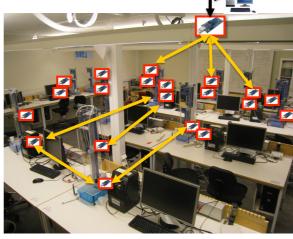
Test-bed for control over IEEE 802.15.4

20 coupled water tanks connected over wireless multi-hop network

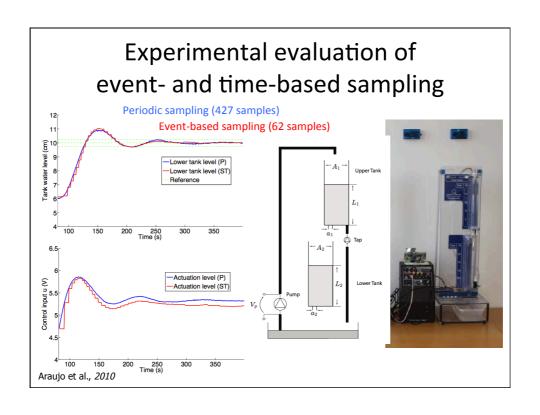
Test-bed to evaluate new control technology and











- Process industry
- Transportation systems
- Smart buildings

Goods Transportation: Societal Perspective

 Goods transportation accounts for 30 % of CO₂ emissions

15 % of greenhouse gas emissions of the global fossil fuel combustion



Goods transport is projected to increase by 50% for 2000-2020

International Transport Forum (2010), European Commission (2006)

Goods Transportation: Fleet Owners Perspective





Total fuel cost 80 k€/year/vehicle

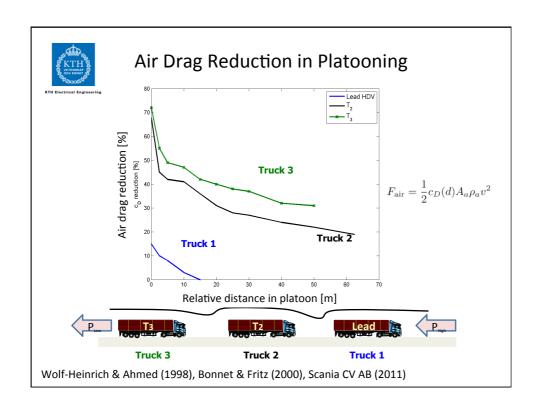
Schittler (2003)

Automated Platooning as a Solution

- May tripple highway throughput
- May reduce fatalities by 10%
- May reduce emissions by 20%



Varaiya et al., PATH project (2010), Robinson et al., (2010)

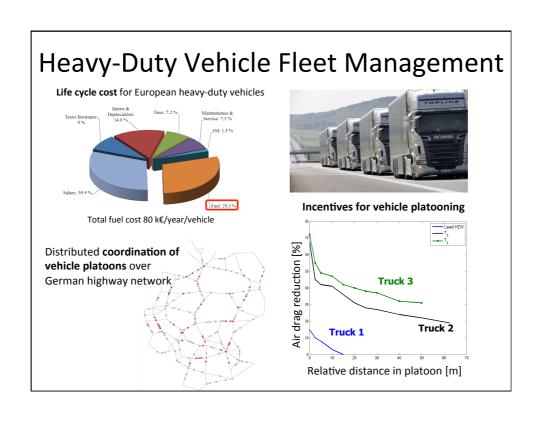


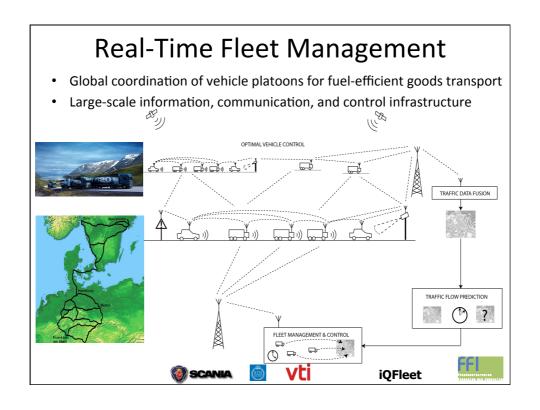
Collaborative Driving for Fuel Reduction

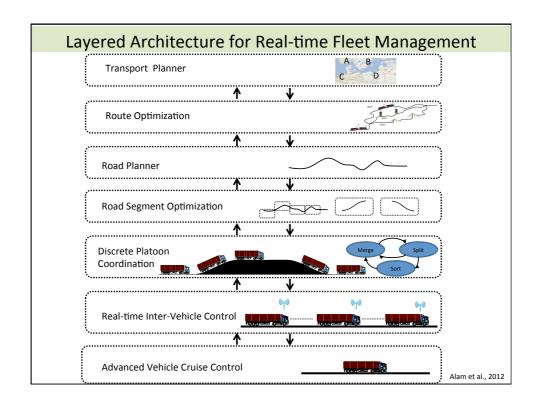


- Drive closer together to **reduce air drag** and prepare vehicles based on road and traffic information
- Enabled by new communication and sensor technologies
- Safety guarantees through automatic control

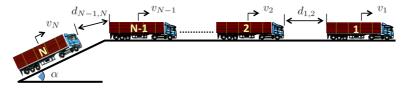




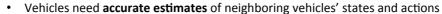




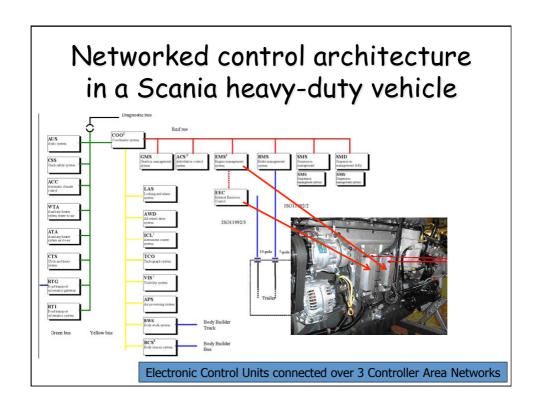
Networked Control in Platooning

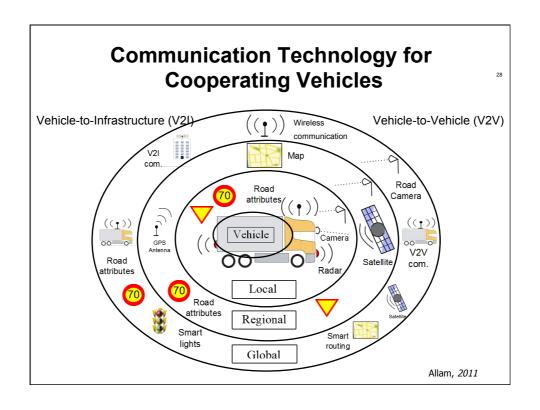


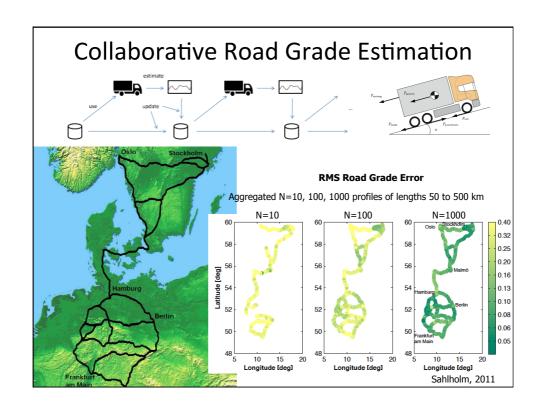
- Platooning control applications require **collaborative actions**
 - Fuel-efficient adaptive cruise controllers
 - Collaborative route planning
 - Autonomous safety maneuvers

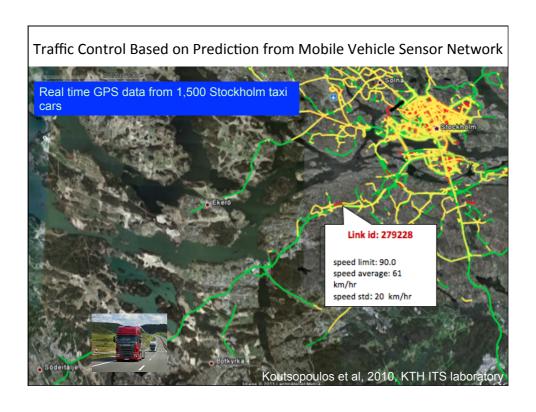


- Control performance is tightly coupled to how well data (position, velocity, breaking estimates) are communicated across the platoon
- How does the communication influence the system performance?
- What is an efficient communication strategy for specific control tasks?













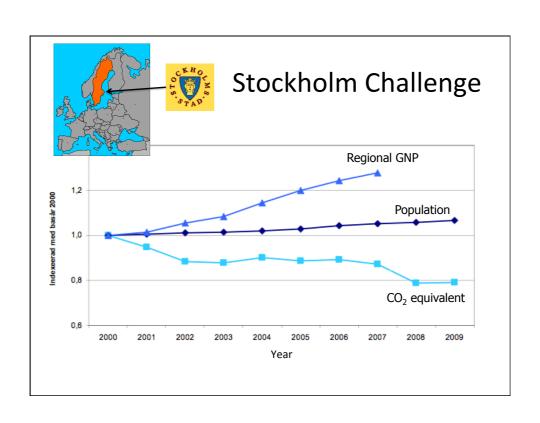
Challenges in Coordinating Heavy-Duty Vehicle Fleets

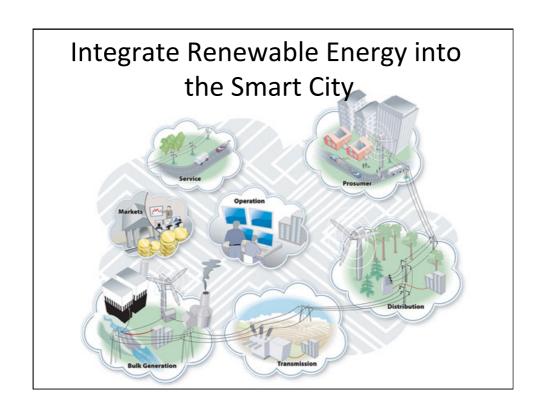
- Pricing of platooning and traffic information services
- Local vs global optimization (vehicular vs societal)
- Integration with existing infrastructure and management
- Safety despite other vehicles and humans in the loop
- V2V and V2I communication and system security
- Standardizations



Tunnel disaster relief scenario IoT technology to support rescue operation at tunnel accident OPERATION ROOM FIRE SENSOR DATEWAY NOOR VIDEO VIDEO

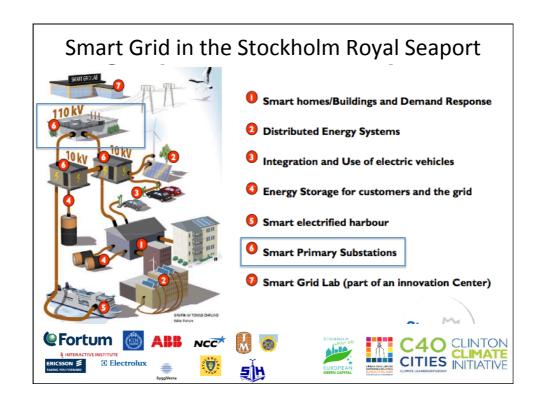
- Process industry
- Transportation systems
- Smart buildings

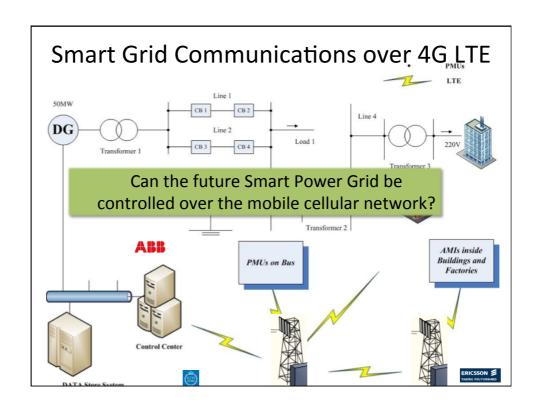


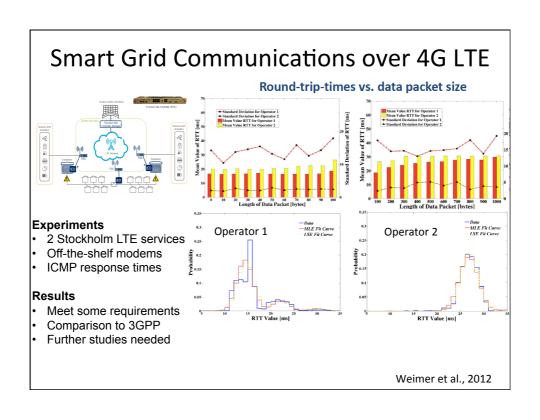


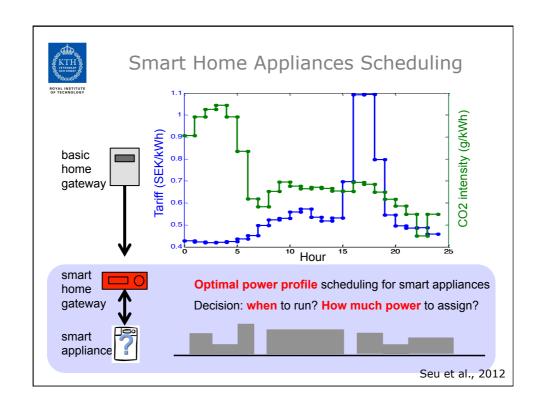


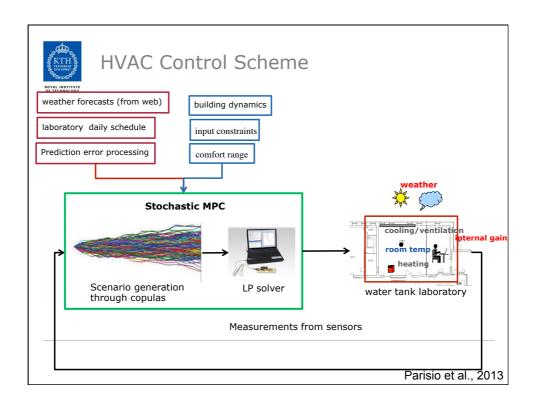


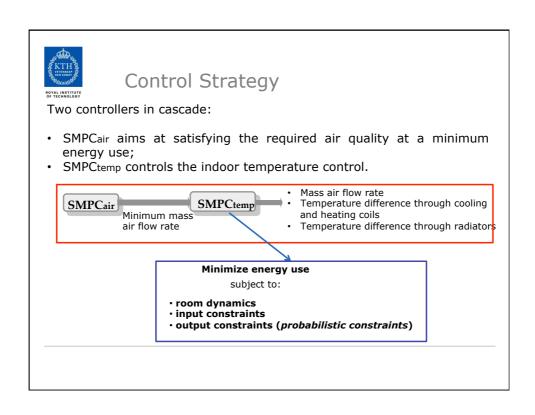


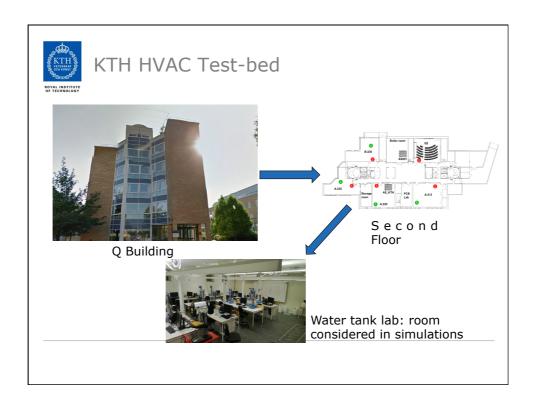














Compared Control Strategies

• Performance Bound (PB) MPC:

an ideal MPC, used as a theoretical benchmark, endowed with error-free forecasts;

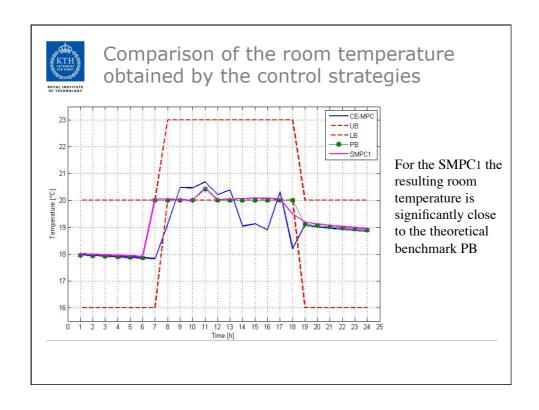
• Certainty Equivalence (CE) MPC:

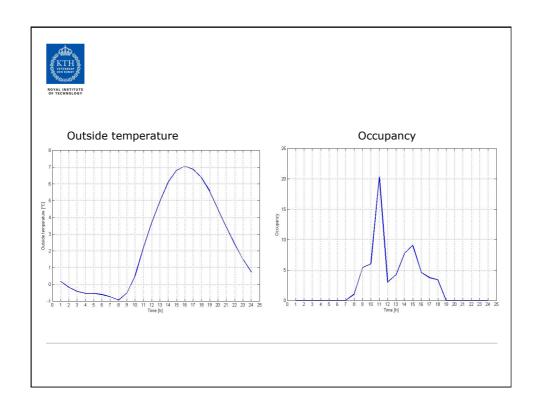
a common practice MPC that simply neglects the uncertainties in the forecasts;

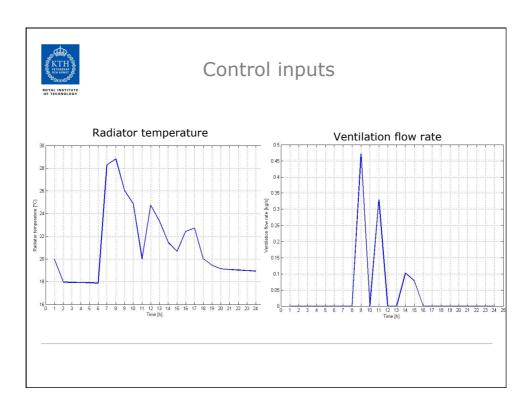
• Stochastic Model Predictive Control (SMPC):

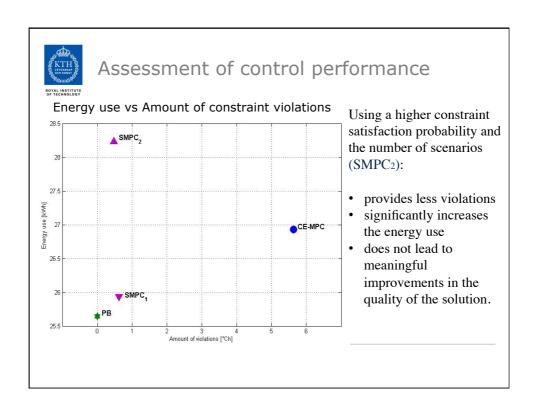
the MPC that uses the copula-based scenarios od random variables (i.e., outside temperature, radiation, occupancy).

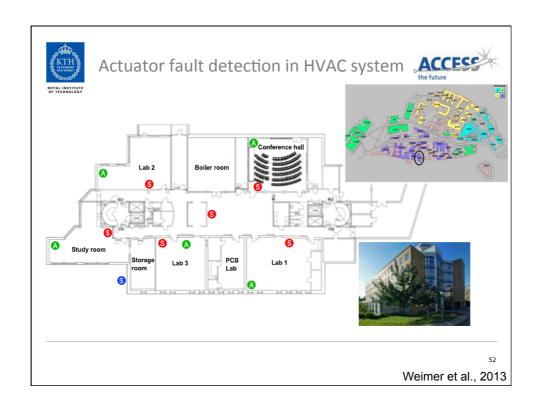
We simulate an SMPC with 60 scenarios and a 91% of constraints satisfaction level (SMPC₁) and an SMPC with 120 scenarios and a 94% of constraints satisfaction level (SMPC₂).

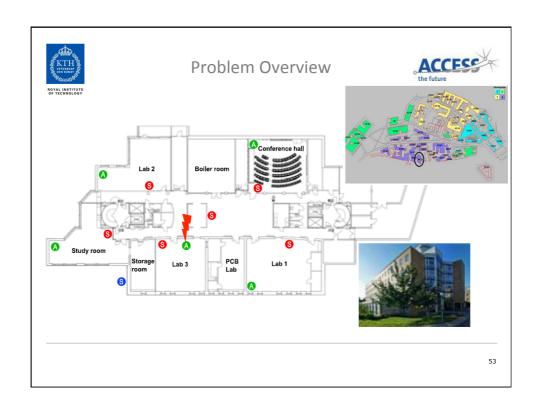


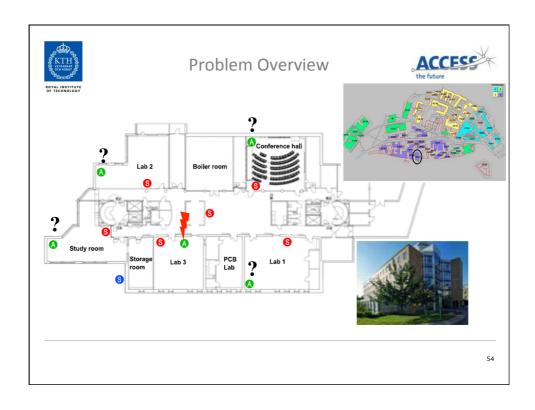


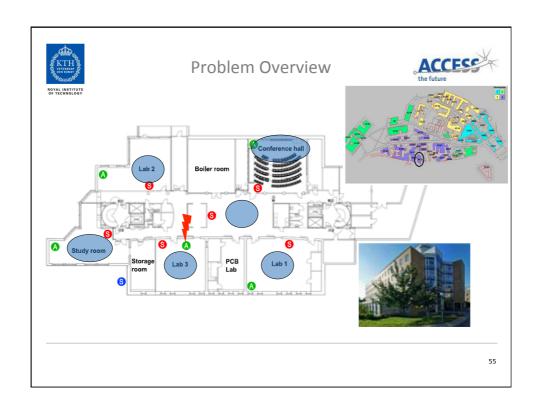


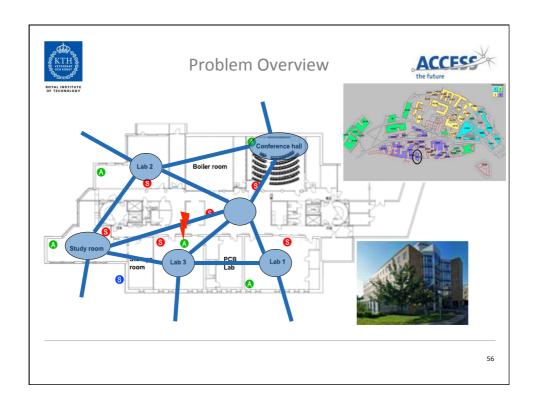


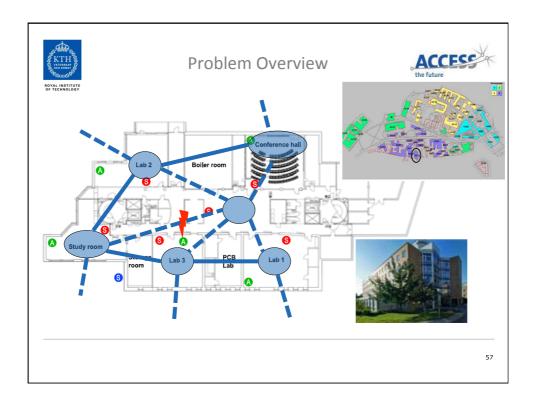














Problem Formulation



$$x_{j}(k+1) = x_{j}(k) + m_{j} \sum_{i \in \mathcal{N}_{j}} a_{ji} \Big(x_{i}(k) - x_{j}(k) \Big) + b_{j} d_{j}(k) + w_{j}(k)$$
(first-principles model)

 $y_j(k) = x_j(k) + v_j(k)$

- x = zone temperature
- y = temperature measurement
- w, v = Gaussian noises
- m = zone mass
- a = inter-zone gain
- b = actuator gain
- d = actuator input

$$egin{aligned} oldsymbol{y}_j &:= \left[y_j(0), \dots, y_j(T)
ight]^{ op} \ oldsymbol{d}_j &:= \left[d_j(0), \dots, d_j(T)
ight]^{ op} \end{aligned}$$
 (time-series)

58



Problem Formulation



$$x_j(k+1) = x_j(k) + m_j \sum_{i \in \mathcal{N}_j} a_{ji} \Big(x_i(k) - x_j(k) \Big) + b_j d_j(k) + w_j(k)$$

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- x = zone temperature
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ight]^ op \ oldsymbol{d}_j \coloneqq \left[d_j(0),\ldots,d_j(T)
ight]^ op \ ext{(time-series)}$$

actuator input structure $oldsymbol{d}_\ell = heta_\ell \mathbf{1} + \mu_\ell oldsymbol{u}_\ell$

59



Problem Formulation



$$x_j(k+1) = x_j(k) + m_j \sum_{i \in \mathcal{N}_j} a_{ji} \Big(x_i(k) - x_j(k) \Big) + b_j d_j(k) + w_j(k)$$
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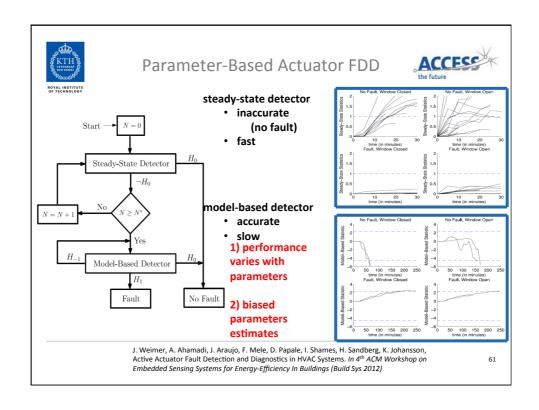
actuator input structure

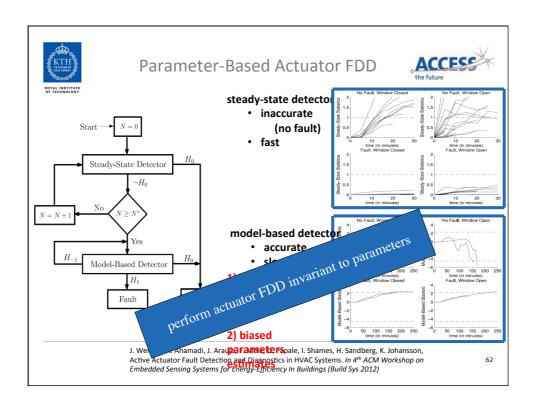
 $\boldsymbol{d}_{\ell} = \theta_{\ell} \mathbf{1} + \mu_{\ell} \boldsymbol{u}_{\ell}$

hypothesis test

H0: $\mu_{\ell} = 1$ H1: $\mu_{\ell} = 0$

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Problem Formulation

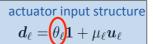


$$x_j(k+1) = x_j(k) + m_j \sum_{i \in \mathcal{N}_j} a_{ji} \Big(x_i(k) - x_j(k) \Big) + b_j d_j(k) + w_j(k)$$

(first-principles model)

- $y_j(k) = x_j(k) + v_j(k) \label{eq:yj}$ x = zone temperature
- y = temperature measurement
- w, v = Gaussian noises
- m = zone mass
- a = inter-zone gain
- b = actuator gain (Unknown)
- d = actuator input

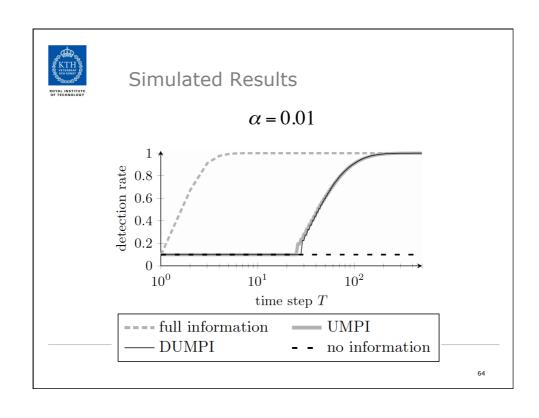
$$egin{aligned} oldsymbol{y}_j &:= \left[y_j(0), \dots, y_j(T)
ight]^{ op} \ oldsymbol{d}_j &:= \left[d_j(0), \dots, d_j(T)
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 (time-series)

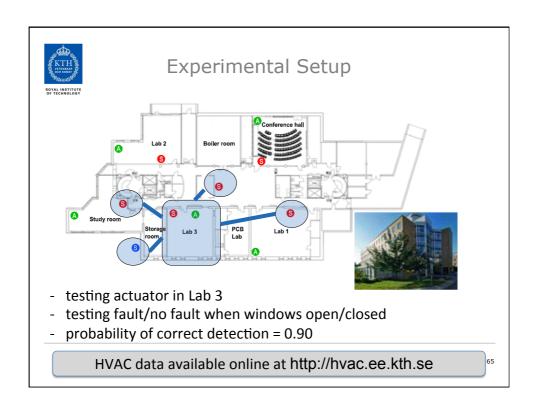


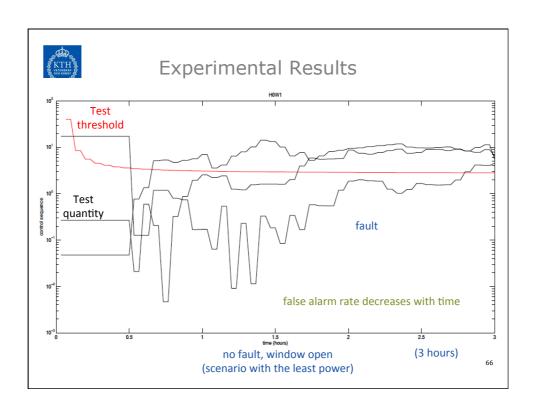
hypothesis test

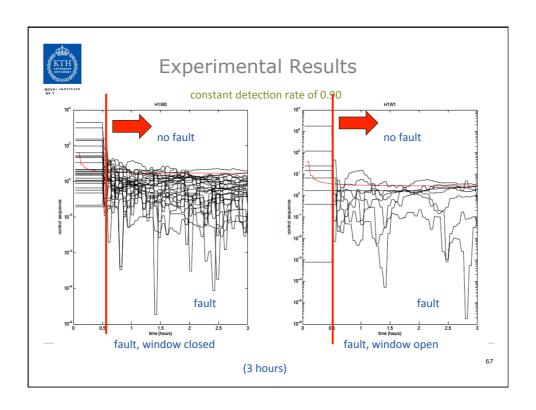
H0: $\mu_{\ell} = 1$ H1: $\mu_{\ell} = 0$

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- Process industry
- Transportation systems
- Smart buildings