Advanced Process Control

From processing industries to embedded applications

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Outline of the talk

Model based control
- Honeywell Prague laboratory activities
- Role of APC/MPC in control system hierarchy

Development of MPC and RTO technology
- Inspired by applications
- Concepts, not technicalities

Embedded applications
- Diesel engine control
- Vapor-liquid cycle control and optimization

Final remarks

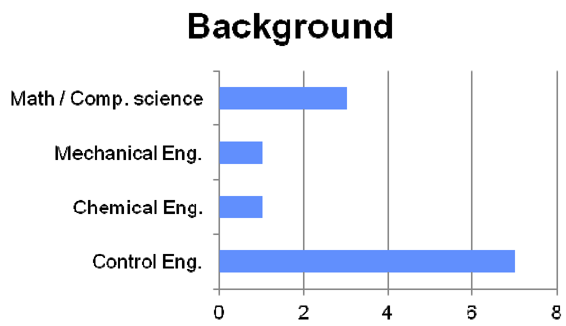
Honeywell Prague Lab History

HPL Founded in 1995

- Process Control & Optimization group
  - APC/ RTO methods and applications
  - First-principles model based
- Data centric group
  - Empirical models, analytics
  - “Big Data”

PCO group activities in APC/RTO area

- Applications in refining/chemical industry
  - 1000+ running MPC applications / Profit Suite
  - Typical sampling period order of minutes
  - 50-100 MVs/DVs/CVs
- Advanced Energy Solution – from 2000
  - Sampling periods order of seconds
  - 10+ MVs/DVs/CVs
  - Integration with RTO (ELA, TLC …)
- Embedded applications – from 2010
  - Sampling periods order of 10 ms, similar size
  - Automotive (Diesel engine air path, after treatment, heat management)
  - Heat pumps, Li-ion battery / power train
  - Lightweight cyber security

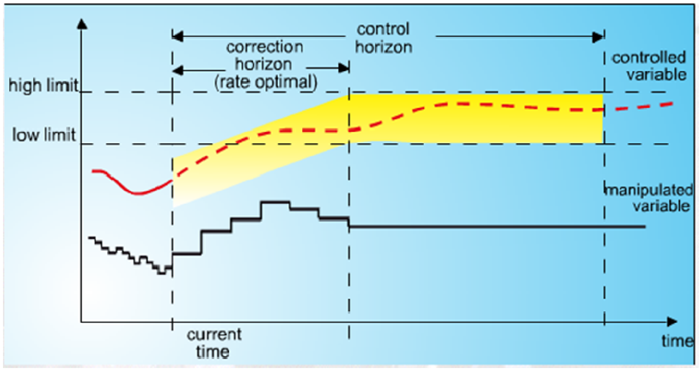


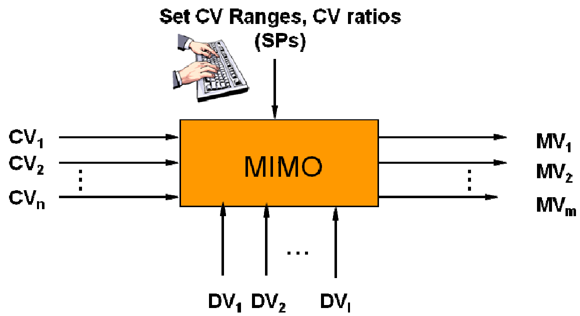
Capabilities

- Domain knowledge (automotive, energy efficiency, combustion, thermodynamics)
- Advanced Multivariable Control and Real-Time Optimization methods and solutions
- Estimation and filtering, virtual sensing
- Embedded algorithm and engineering design tools
- Production code maintenance
- Compliance to automotive standards
- Customer support

Model based control

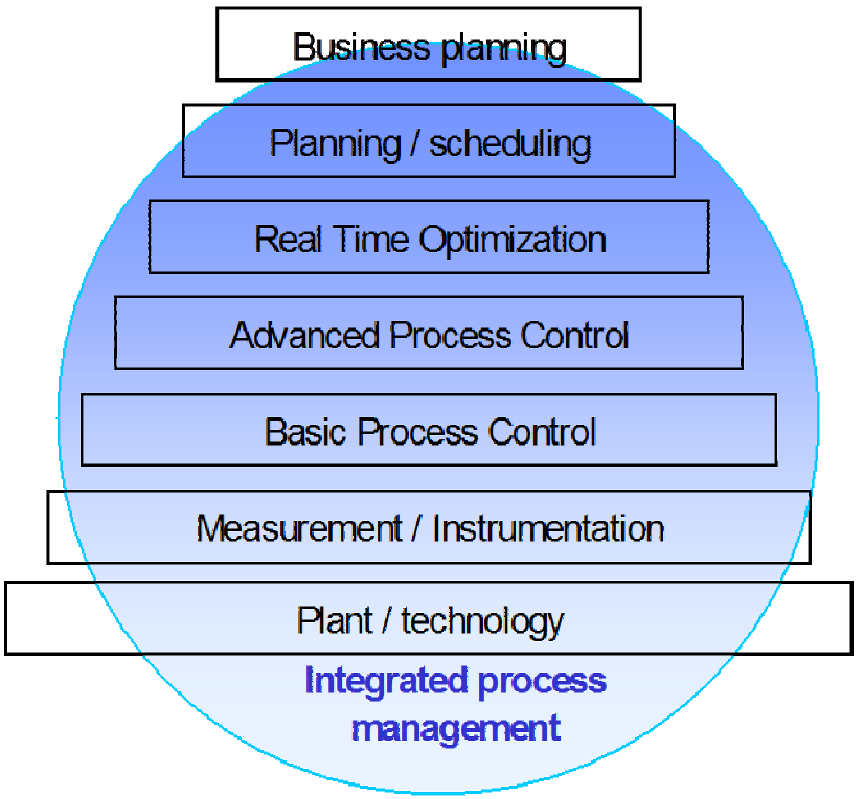
- Model-based Predictive Control (MPC)
  - First advanced control concept widely accepted by industry
  - Multivariable controller
    - Interactions between MVs and DVs
    - Future reference and disturbance “preview” (predictive vs. reactive control action)
  - Reflects multi objective process control nature (controller design vs. control strategy design)
    - Set point tracking
    - Ratio control
    - Constraints handling
    - Optimization
  - Developed by industry, interest from academia came later
    - From simple I/O models to state-space
    - More efficient algorithms (fast QP, IP)
    - Stability analysis
    - Explicit MPC concept





APC/MPC in process control hierarchy

- Advanced process control
  - Coordination of individual SISO loops (set points to basic control)
  - Ad-hoc feedback, feedforward, override and cascade strategies
  - Difficult to develop / tune / maintain
  - Today mostly implemented by MPC (systematic design methods and engineering support tools)
- Real Time Optimization
  - Performance / operation economy based models
  - Provides targets to MPC



Outline of the talk

Model based control

Development of MPC and RTO technology

Embedded applications

Final remarks

Extensions of MPC technology

- MPC problem formulation
  - Range control
  - Ratio control

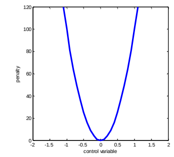
- Model building
  - Model management
  - Closed-loop ID / Active control strategy
  - Stochastic part of the model

- State estimation
  - State-dependent I/O models
  - Unknown input observer
  - Disturbance prediction
  - Estimation under uncertainty

Range Control Concept

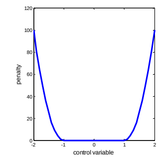
- Output prediction $y = Su + \tilde{y}$
- Set point $y = r$
- Set range $y_{LO} \le y \le y_{HI}$

$$u^* = \arg\min_{u} \left\| Su + \tilde{y} - r \right\|_Q^2 + \left\| \Delta u \right\|_R^2$$



$$u^* = \arg\min_{u,\,z} \left\| Su + \tilde{y} - z \right\|_Q^2 + \left\| \Delta u \right\|_R^2$$

$$y_{LO} \le z \le y_{HI}$$



If feasible

$$u^* = \arg\min_{u} \left\| \Delta u \right\|_R^2$$

$$y_{LO} \le y \le y_{HI}$$

Benefits

- Robustness
  - Minimum effort control (calm control)
- Impact of model uncertainty

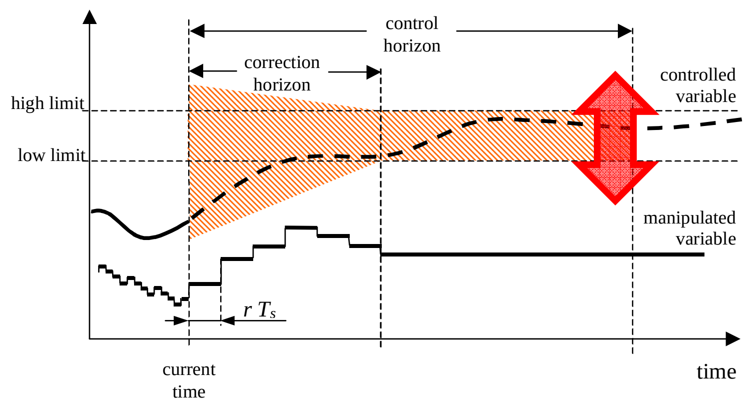
$$y(t) = \sum_{\tau=0}^{N} g(\tau)u(t-\tau) = \sum_{\tau=0}^{N} h(\tau)\Delta u(t-\tau)$$

$$h(t) \approx N\left(\hat{h}(t), \sigma_h^2(t)\right)$$

  - Minimized output uncertainty excitation (“in average”)

$$\operatorname{var}\{y(t)\} = \sum_{\tau=0}^{N} \sigma_h^2(\tau)\Delta u^2(t-\tau)$$

- Additional degrees of freedom for optimization
  - MPC criterion not affected by output changes within the funnel



Ratio control

- Ratio control problem formulation

$$u^* = \arg\min_{u,z} \left\| Su + \tilde{y} - z \right\|_Q^2 + \left\| \Delta u \right\|_R^2$$
$$y_{LO} \le z \le y_{HI}$$

  – Input/rate hard constraints

$$u_L(k) \le u(k) \le u_H(k)$$
$$\Delta u_L(k) \le \Delta u(k) \le \Delta u_H(k)$$

  – Predefined ratio of given CVs (hard constraints on ratio)

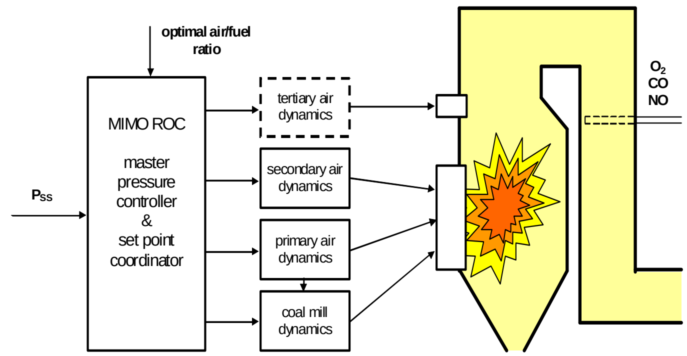
$$\frac{y_i(k)}{y_j(k)} = c_{ij}(k) \quad \rightarrow \quad \min \sum_k \left(y_i(k) - c_{ij}(k) y_j(k) \right)^2$$

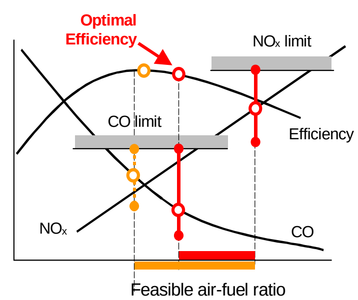
  – Translated into criterion (soft constraints on ratio)

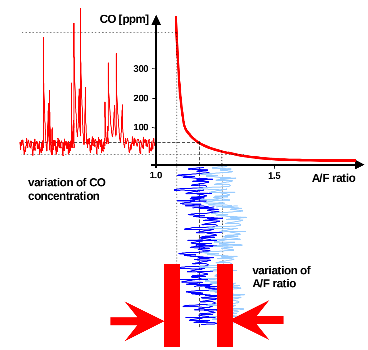
$$\left\| \begin{bmatrix} \mathbf{I} & -\mathbf{C} \end{bmatrix} \begin{bmatrix} \tilde{\mathbf{y}}_1 + \mathbf{S}_1\mathbf{u} \\ \tilde{\mathbf{y}}_2 + \mathbf{S}_2\mathbf{u} \end{bmatrix} \right\|_Q^2 =$$

$$= \left\| \begin{matrix} \tilde{\mathbf{y}}_1 + \mathbf{S}_1\mathbf{u} \\ \tilde{\mathbf{y}}_2 + \mathbf{S}_2\mathbf{u} \end{matrix} \right\|^2_{\begin{bmatrix} Q & -QC \\ -C^T Q & C^T QC \end{bmatrix}} = \left\| \tilde{\mathbf{y}} + \mathbf{S}\mathbf{u} \right\|^2_{\mathbf{Q}_C}$$

  – Required by many applications, still linear MPC problem
  – *V. Havlena and J. Findejs, Application of model predictive control to advanced combustion control. IFAC CEP, 2005*







- Low NOx/optimal efficiency burning
  - Reduced excess air (O2 in flue gas)
  - Reduced A/F variation
- Ratio control
  - Air/fuel "burner nozzle flow" coordination
- Calm control – improved coordination performance

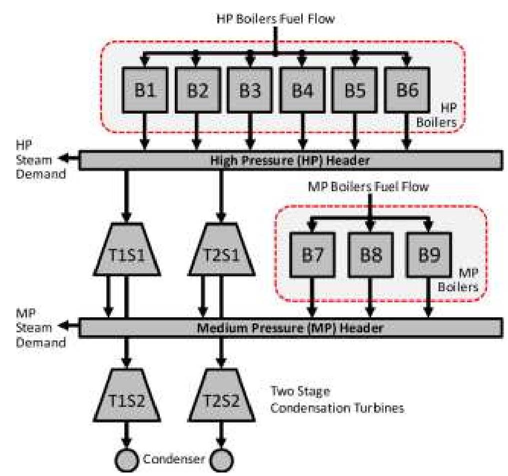
Model building & management

Engineering tools for MPC application

- Chemical / refining
- Black box ID
  - Step testing + FIR/TF matrix estimation
- Seed models + closed loop ID
  - Long open-loop step testing not feasible

First-principle based tools introduced

- Power gen, industrial energy
- Grey-box ID
  - Structure from first principles – robustness
  - Calibration by experimental & historical data
  - *Trnka and Havlena: Subspace like identification incorporating prior information. Automatica, 2009.*



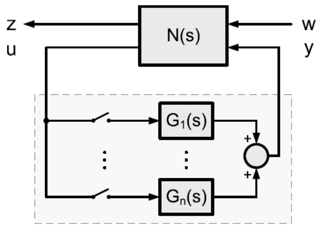
Still not scalable

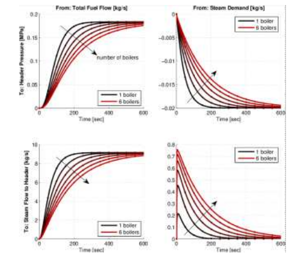
- Different dynamic response of the process for different unit commitment (e.g. parallel units)
- Switching between fixed models obtained by step testing
  - Explosive number of combinations …
  - All configurations not available for testing

Model building & management

Component-based system model

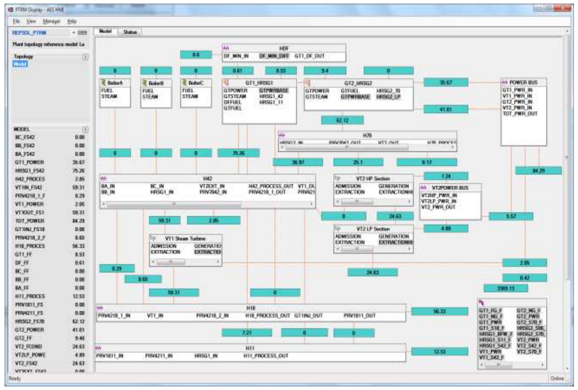
- Combine component models of active components
  - Order reduced with respect to closed-loop performance
- Structure-preserving order reduction (LMI)
  - Automatic just-in time update of MPC model
  - *Trnka et al., Structured Model Order Reduction of Parallel Models in Feedback, IEEE CST, 2013*

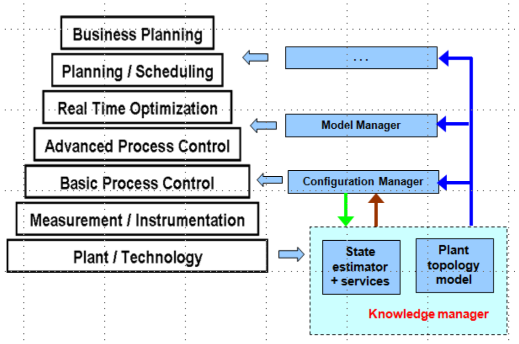




Plant Topology Reference Model

- Engineering tool
  - Configure topology
  - Set up “unit on” logic
  - Stream properties (RT pricing)
- Run-time engine
  - Real time responsiveness to process changes
  - OPC UA support (time triggered data → events)
- Consistency of individual layers
  - Dynamic/steady state models





Other model enhancements

Active model update

- Sustained benefits from APC/RTO
  - Loss of performance / model mismatch
- Model update in closed loop (MPC running)

$$J^*_{MPC}(u^*) = \min_{u} \|Su + \tilde{y} - r\|^2_Q + \|\Delta u\|^2_R$$

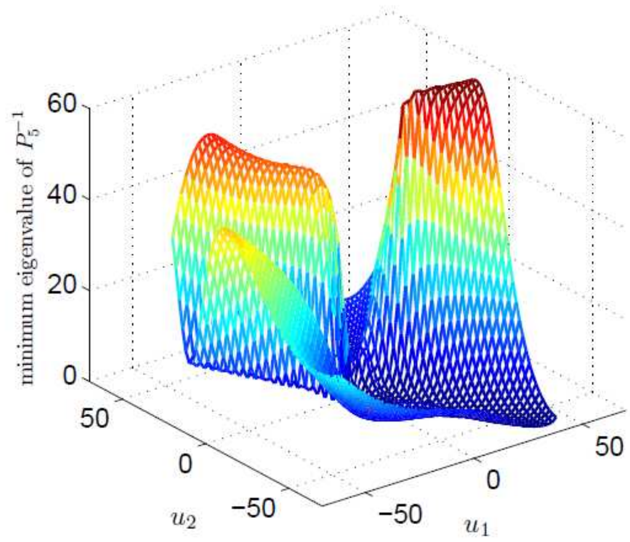
  - Perturbation δu of baseline MPC solution u^* (multiple step solution)
  - Information matrix maximization

$$\max_{\delta u} P^{-1}_{\theta}(t_0 + T)$$

such that

$$\|S(u^* + \delta u) + \tilde{y} - r\|^2_Q + \|\Delta(u^* + \delta u)\|^2_R \leq (1+\alpha) J^*_{MPC}(u^*)$$

  - GACR project "*Feasible approximation of dual control strategies*"
  - *Rathousky et al., MPC-based approximate dual controller by information matrix maximization. IJACSP 2013.*



Minimum eigenvalue of information matrix $P^{-1}(t+5)$ as a function of $\delta u(t+1)$ and $\delta u(t+2)$ perturbation

Other model enhancements

Stochastic part of the process model

$$Y(z) = G(z)U(z) + H(z)E(z)$$

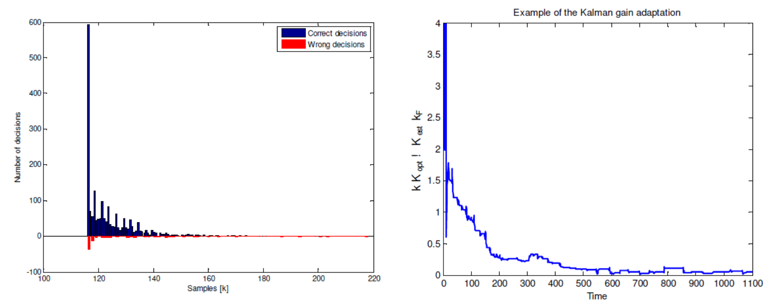
- Simplest case: *H* defined by noise covariance

$$x_{k+1} = Ax_k + Bu_k + w_k \qquad \operatorname{cov}\left\{\begin{bmatrix} w_k \\ e_k \end{bmatrix}\right\} = \begin{bmatrix} Q & 0 \\ 0 & R \end{bmatrix}$$
$$y_k = Cx_k + Du_k + e_k$$

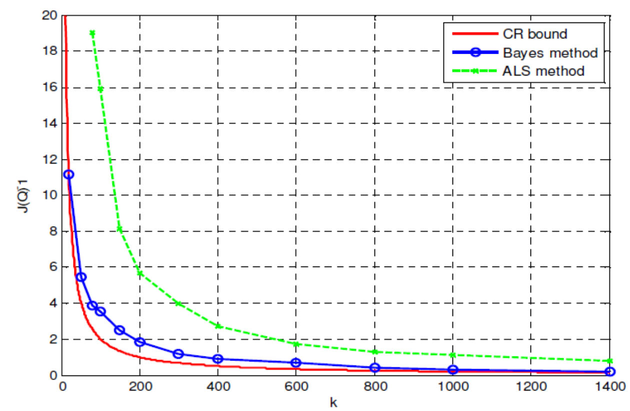
$$G(z) = C(zI - A)^{-1}B + D$$

$$H(z)\Sigma_e H^T(z^{-1}) = C(zI - A)^{-1}Q(z^{-1}I - A)^{-T}C^T + R$$

- *Q*/*R* knowledge critical for Kalman filter tuning
  - KF performance monitoring
    (sequential prediction error testing – white noise)
  - Detection of performance degradation
  - Bayesian update of Q/R matrices and Cramer-Rao bound for Q/R estimates developed
  - *Matisko et. al, Noise covariance estimation for Kalman filter tuning using Bayesian approach and Monte Carlo. IJACSP, 2013*



Sequential testing of KF performance and Kalman gain adaptation results (difference from optimal value)



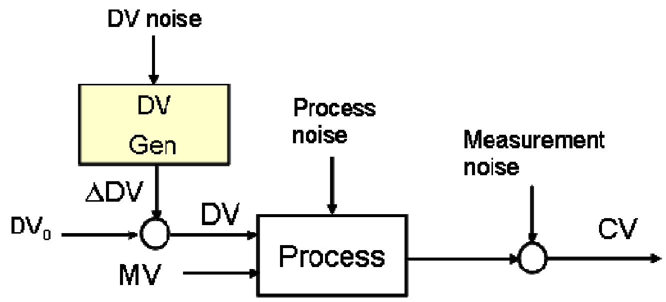
Comparison of C-R bound for Q matrix estimation

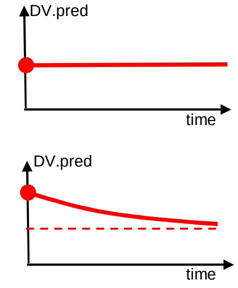
Odelson et al., A new autocovariance least–squares method for estimating noise covariances. Automatica, 2005

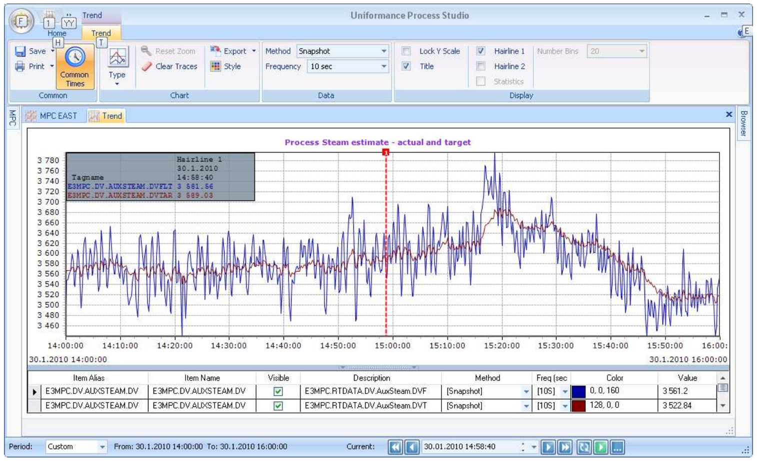
Non-measurable disturbances

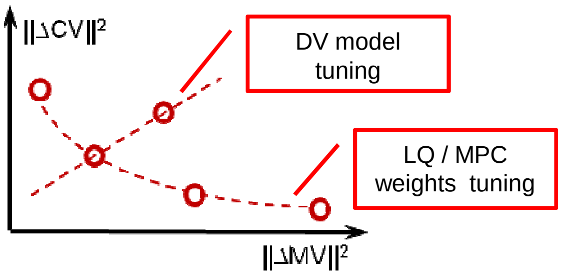
DV models used

- KF as unknown input observer
- Typical model – random walk
  - Predicted future value = current value (constant)
  - Offset-free tracking achieved by integral action in the controller
  - Overcompensation
    (e.g. pulse disturbances from PRVs)
- More realistic model - separate current and steady state value
  - Full predicted trajectory used
  - Significant improvement of control performance in large multi header systems (SASOL 9 x 550 t/h boilers)
  - Another DoF for controller tuning
  - Calm control









Kalman filter for models with uncertain parameters

Inferential sensing robustness

Inferred values depend strongly on model quality

- Mismatch in model dynamics results in fake “artifacts” during the transients

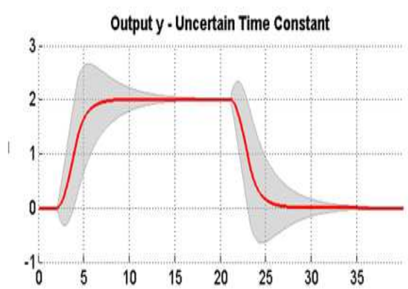
Kalman filter for uncertain systems

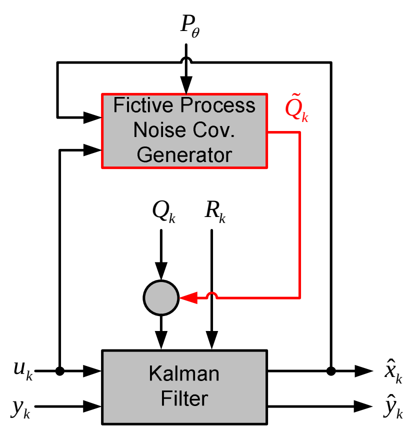
$$x(k+1) = A(\theta)x(k) + B(\theta)u(k)$$
$$y(k) = C(\theta)x(k) + D(\theta)u(k)$$

$$\mathrm{var}(\theta_i) = \sigma_{i,i}^2$$

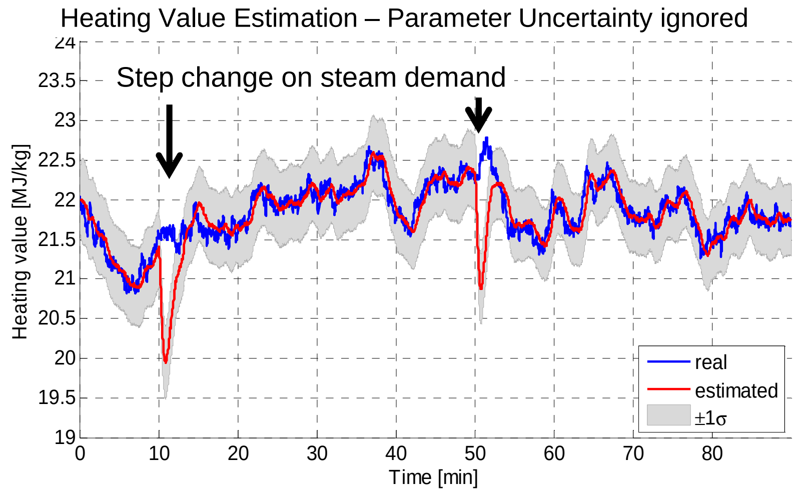
- Equivalent noise concept

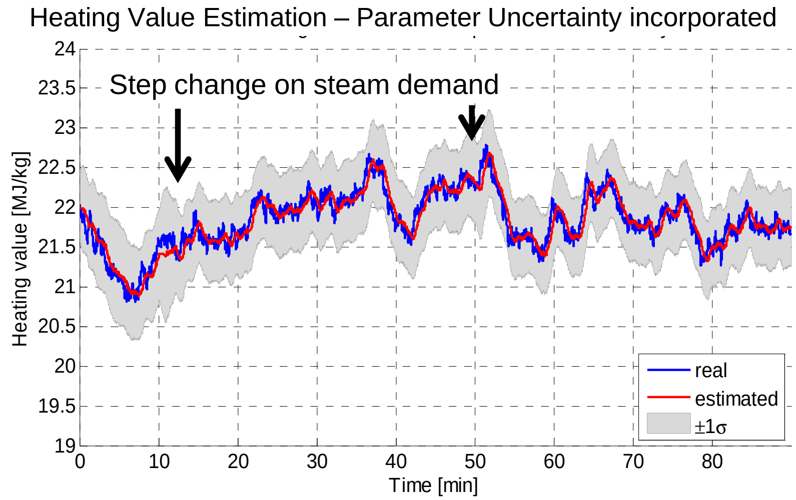
$$Q_{(i,i)}(k) = \sigma_{i,i}^2 \begin{bmatrix} \frac{\partial A}{\partial \theta_i} & \frac{\partial B}{\partial \theta_i} \end{bmatrix} \begin{bmatrix} x(k) \\ u(k) \end{bmatrix} \begin{bmatrix} x(k) \\ u(k) \end{bmatrix}^T \begin{bmatrix} \frac{\partial A}{\partial \theta_i} & \frac{\partial B}{\partial \theta_i} \end{bmatrix}^T \qquad Q(k) = \sum_{i=1}^{p} Q_{(i,i)}(k)$$





- *Trnka, Havlena: Biomass co-firing with inferential sensor. IFAC Symposium Power Plant and Power System Control, 2012*





Outline of the talk

Honeywell Prague laboratory

Model based control

Development of MPC and RTO technology

Embedded applications

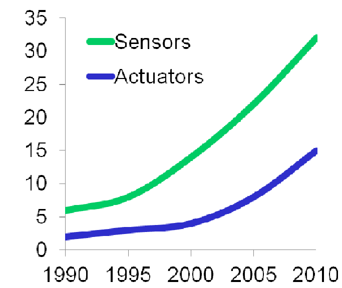
- **Diesel engine air-path control**

Final remarks

Automotive Control Design

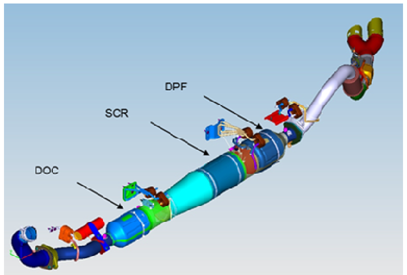
Trends driving applications of advanced control

- Engine / aftertreatment complexity
- Tighter environmental requirements
- Demand outpacing supply



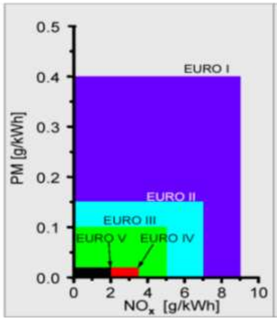
Benefits of MPC

- Multivariable interactions taken into account
- Reduced calibration requirements
- Actuator and engine state constraints
- Robustness to model uncertainty

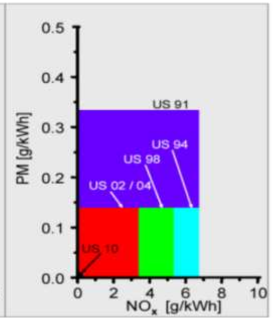


Advanced Control Remains Elusive

- Difficult to implement the run-time component in ECU
- Designing & calibrating advanced control still complex
- **OnRamp Design Suite**
  - **Solve both of these problems**



Europe

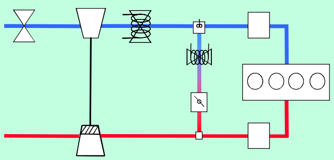


U.S.

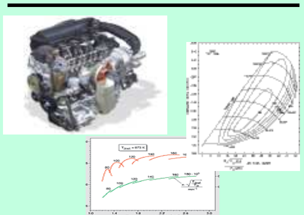
OnRAMP design suite

Software Tool for Automatic Generation of Models and Optimal Control Algorithms

Model Structure



Measured Data



Control Design

RP System or ECU

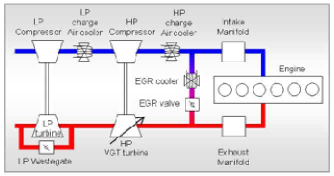
Optimal Multivariable Controller

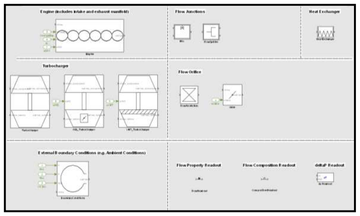
Systematic procedure for advanced control design
Complexity hidden from end user, math remains behind the scene
Need for robust ID and optimization algorithms

Engine Air Path Model

Model structure

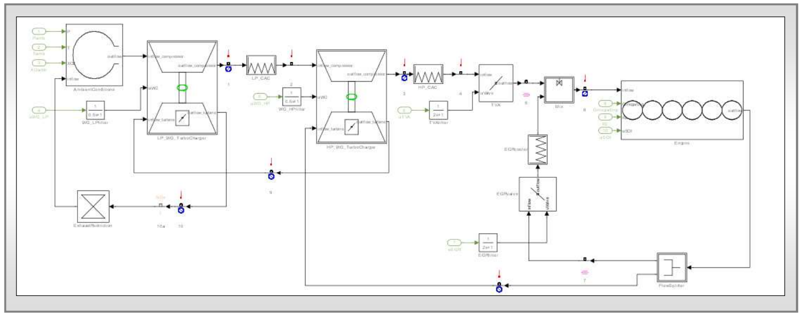
- Simulink component library
- Engine topology translates to Simulink diagram directly
- Flow lines transmit all variables (p, T,…)

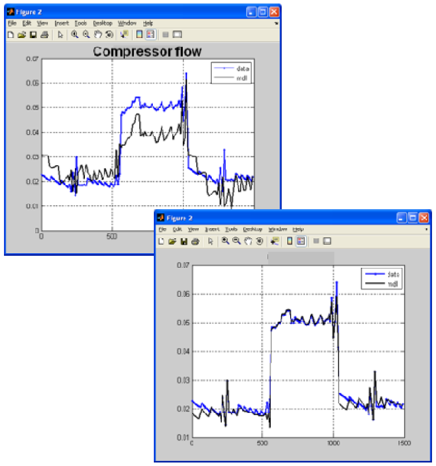


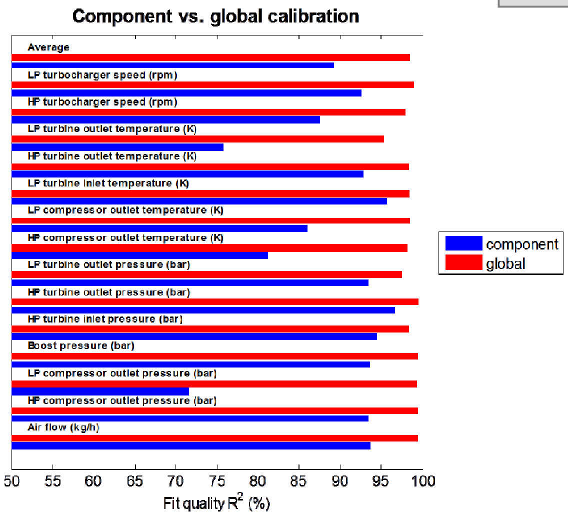


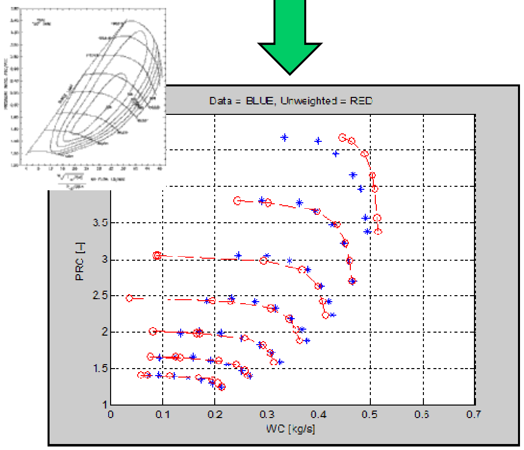
Component + experimental data

- Component model fit
- Global level fit
  - Slack variables for interconnections and internal component constraints (regularization)
  - Appx. 450 equilibrium points
- Robust method for automated solution

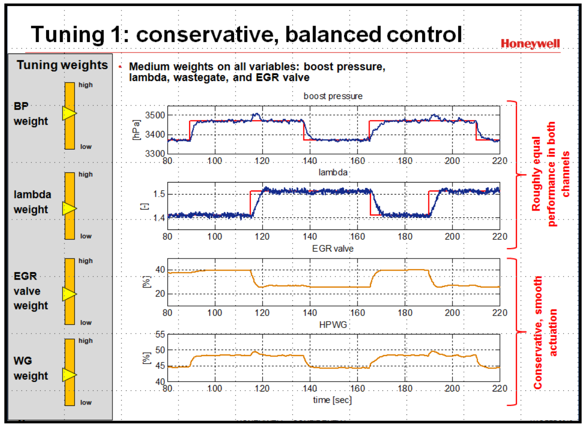


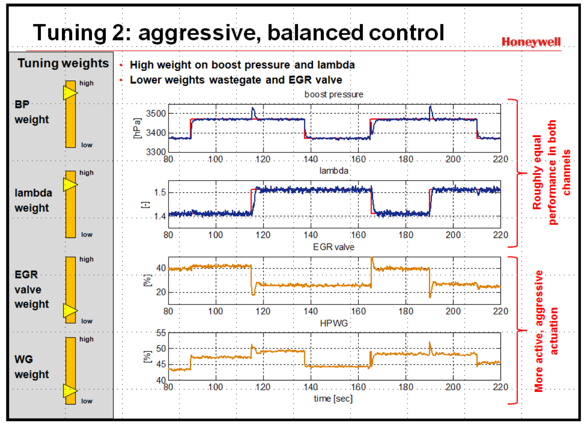


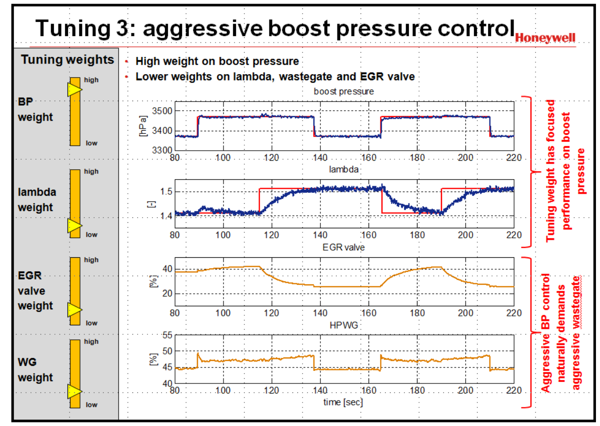




Control design and deployment

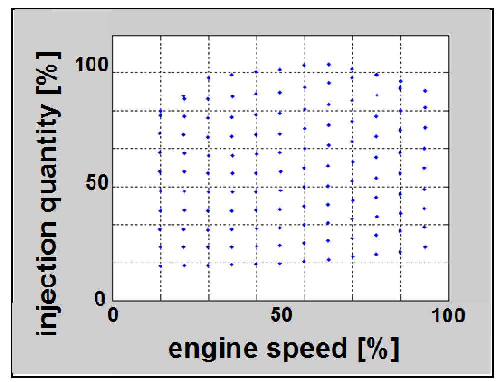






Control tuning

- 2 degrees of freedom, translated to frequency domain
  - Performance (bandwidth)
  - Robustness (non-parametric uncertainty models)
- Uniform performance setting across multiple operating points
  - Grid of speed-fuel points



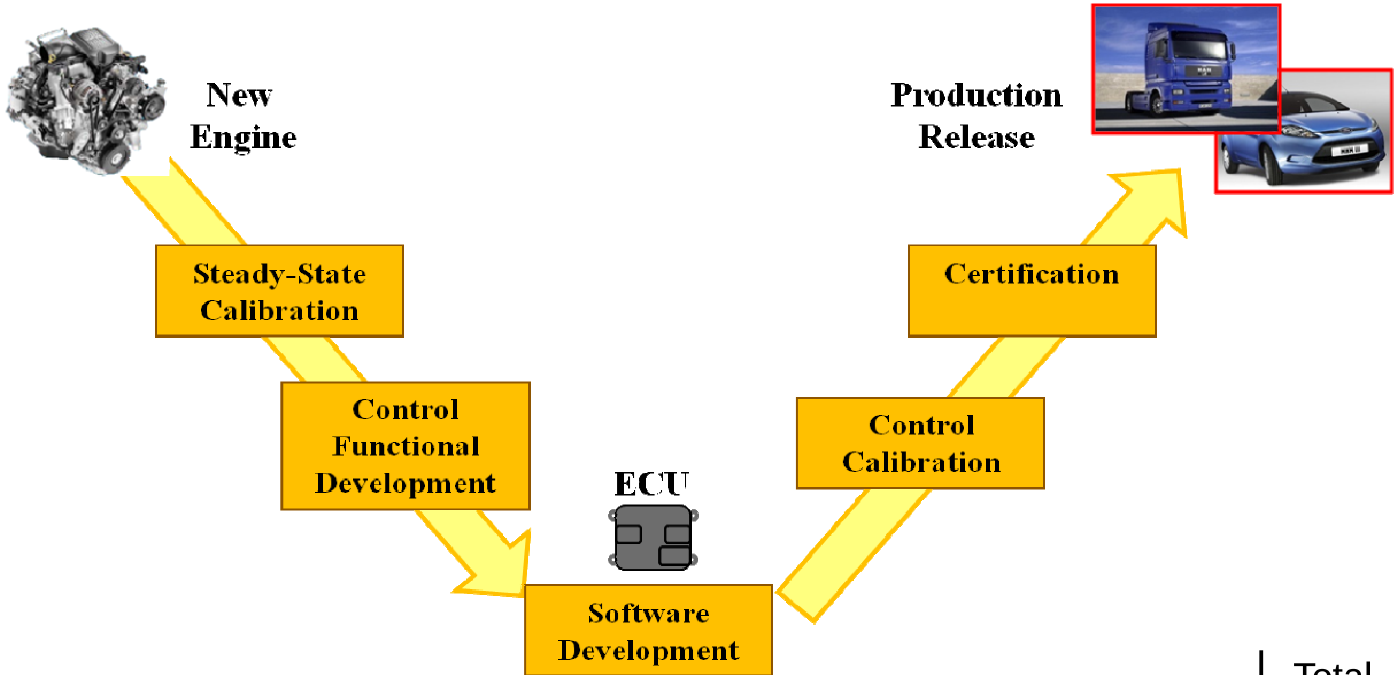
Deployment

- Unified C-code (MISRA compliant)
- Set of models for MPC
- Set of Kalman filters running in parallel

Other benefits

- Flexible change of control strategy (selection of CVs / MVs/ DVs)
- Use of measured vs. inferred variables
- Evaluation on standard drive cycles

Impact on Production Control Development



						Total Development Time
Baseline:	~2 months	~3 months	~6 months	~4 months	~3 months	~18 months
OnRAMP:	**~2 months**	**~1 months**	**0 months**	**~2 months**	**~3 months**	**~8 months**

Model-based On Board Diagnostic still unresolved problem

Outline of the talk

Honeywell Prague laboratory

Model based control

Development of MPC and RTO technology

Embedded applications
- **Thermodynamic vapor-liquid cycle optimization**

Final remarks

Heat pump trends & control objective

Trends

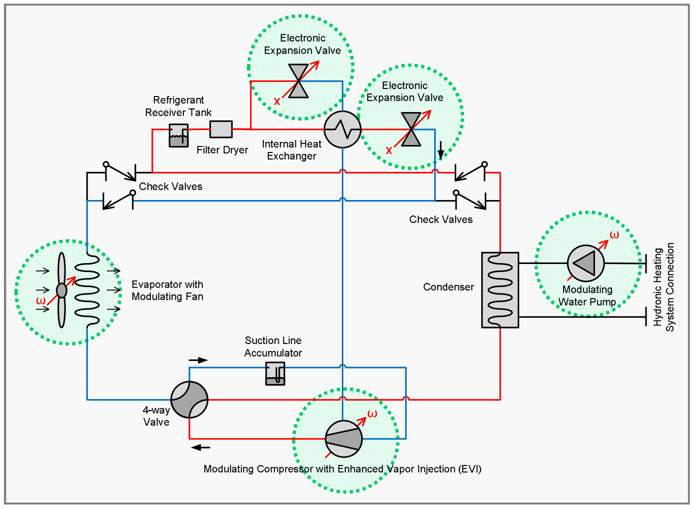
- Modulating components
  (compressors, electronic valves, fans, pumps)
- Complex cycle design
  (vapor injection, internal heat exchangers, multi-stage)
- Available HP control solutions do not follow hardware development to fully use its potential

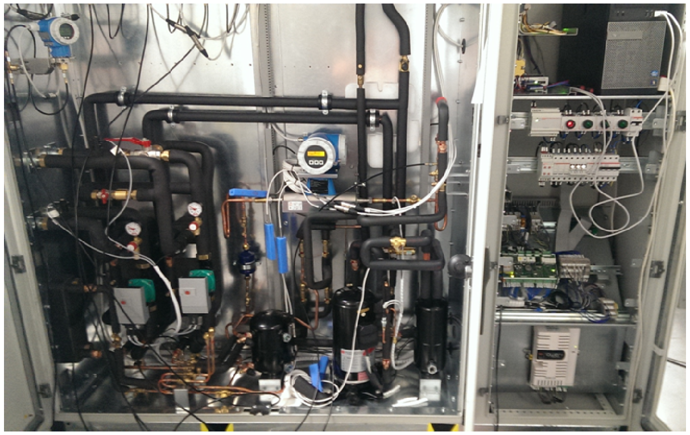
Objectives

- Multi-variable controller achieving maximum year-round performance (seasonal COP)
- Virtual sensor for estimation of evaporator fouling by frost formation
- Optimized defrosting control strategy
- Engineering design suite for rapid controller design
- Applications with pilot customers

Project funded by TA CR (Alfa program)

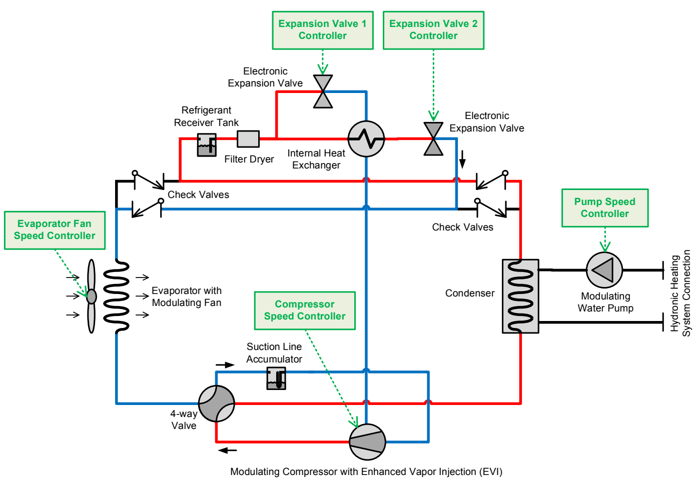
- Collaboration with CTU and test bed in HTS Brno
- HP with extended instrumentation





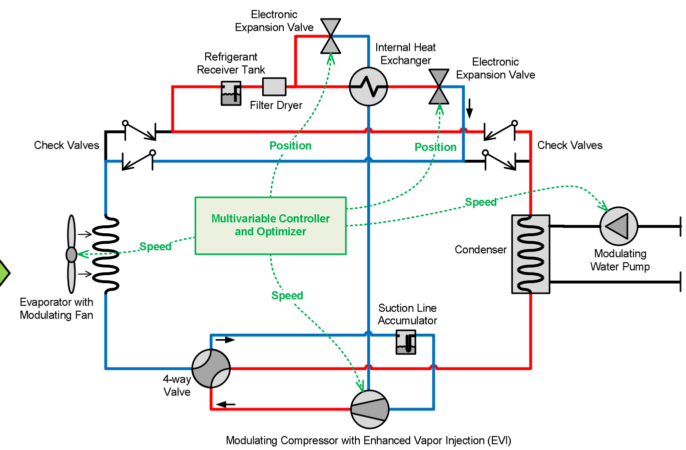
Coordinated Dynamic Control by MPC

- Systems based on thermodynamic vapor cycles have critical constraints:
  - Compressors and turbines must be supplied with superheated vapor (minimum stable superheat)
  - Pumps must be supplied with sub-cooled liquid
  - Safety margins go against efficiency
- Cycle components have strong dynamic interactions
  - Independent (component by component) control loops have poor performance
- Multivariable predictive control
  - Tight control respecting component interactions and constraints (safety margins minimization)
  - Quick optimum recovery after disturbances



Independent control loops

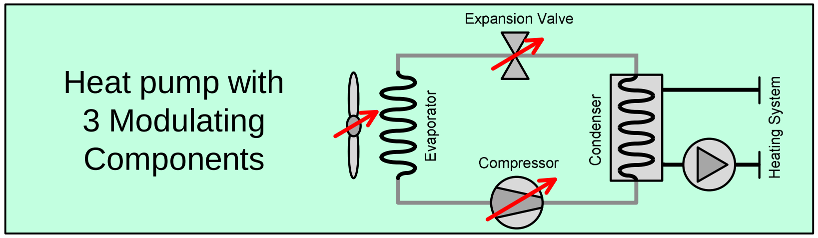
~5% overall efficiency improvement for heat pumps



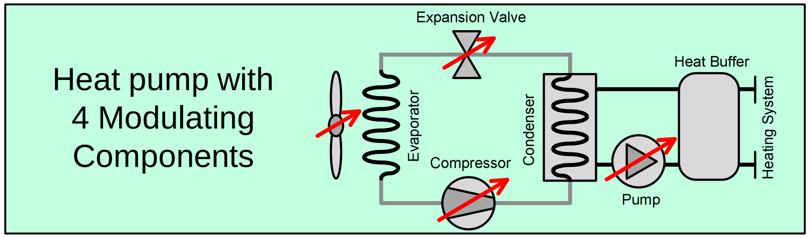
Coordinated multivariable control

Embedded Set Point Optimization

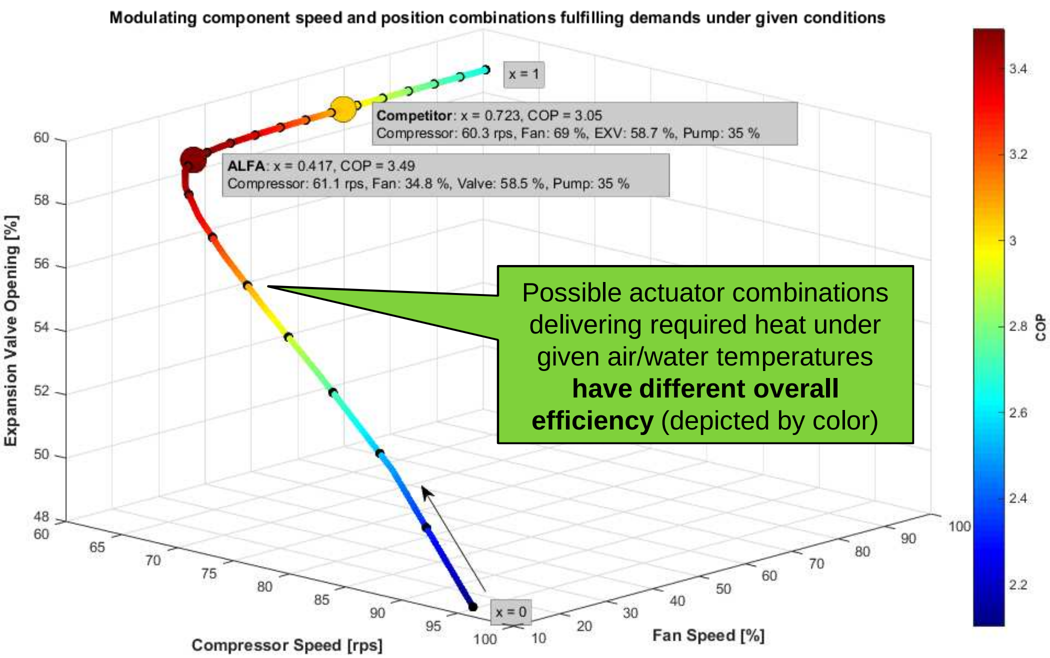
- Systems based on thermodynamic vapor cycles that have sufficient number of actuators have a potential for optimization – requirements can be achieved by different combinations of actuators



1DoF for optimization

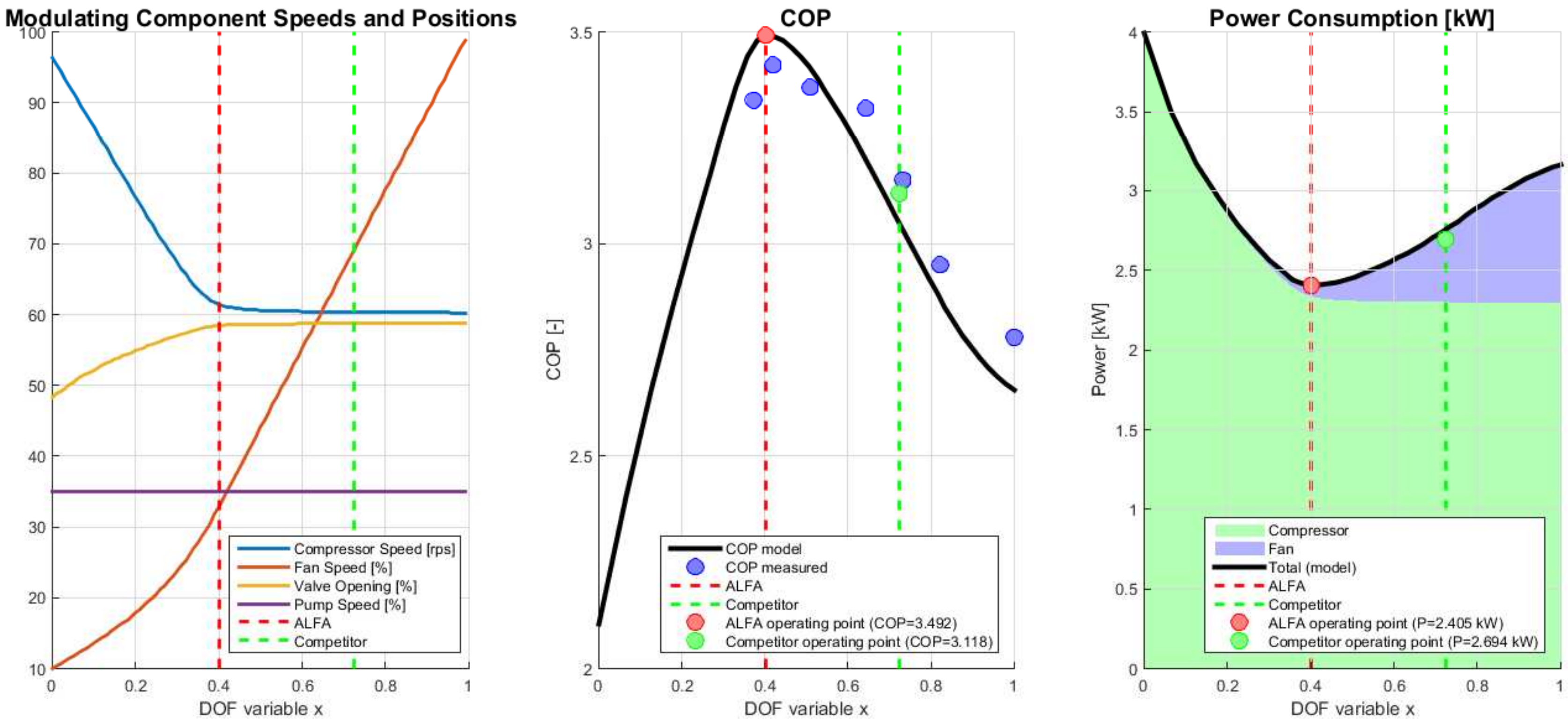


2 DoF for optimization



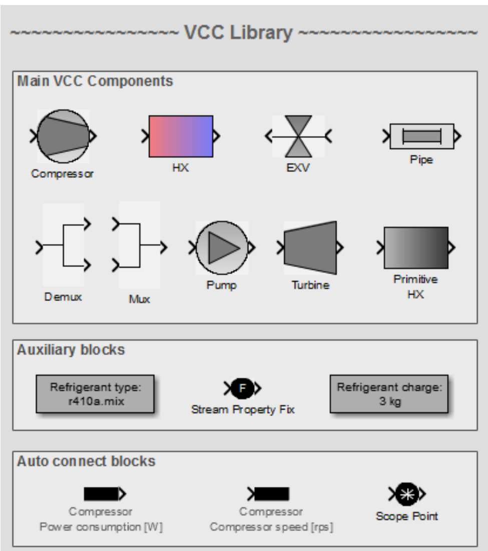
ALFA COP Improvement – A2/W35, 8.4kW, SH 15K, Twin 30℃

- COP improvement in the range from 5 to 15 % against industry standard for HP with 3 modulating components
- Experimental validation confirmed component-based approach
- Standard controller without RTO cannot be tuned for changing conditions

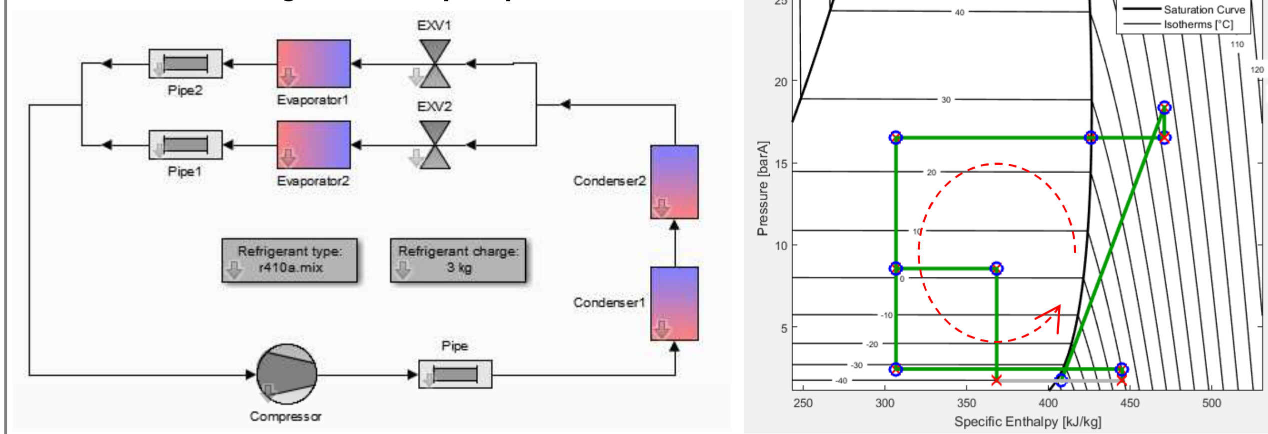


Engineering tools for optimization/control design

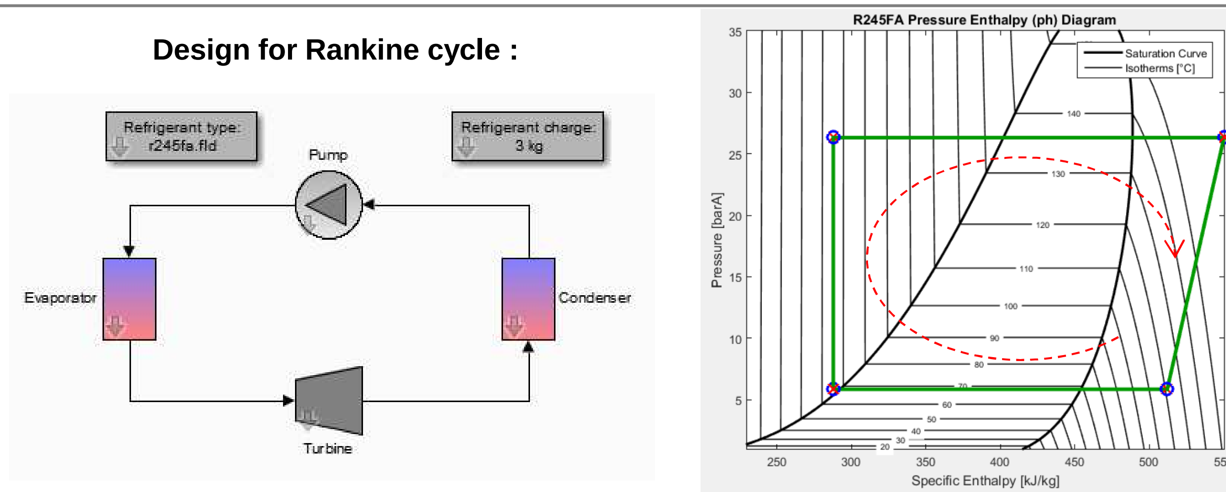
- Engineering tools follow OnRAMP philosophy and workflow
- Application areas
  - Heat pump / AC
  - Waste heat recovery (Rankine cycle)



Design for Heat pumps:



Design for Rankine cycle :



Outline of the talk

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Final remarks

Final remarks

20+ year experience with application and development of advanced control methods, under both academic and industrial research hat

Gap between theory and reality

- Successful applications of model-based control to nontrivial problems requires good understanding of underlying first principles
  - Weak point of current curricula
- Going the whole way to customer pilot projects inspires further development of rigorous theory
  - Matlab-based prototype covers 20-30% effort
- Industry is short/mid term focused
- Longer term problems for PhD students / governmental funding
  - No formal process, personal contacts