The German “Energiewende” – a Systems & Control Perspective

Wolfgang Marquardt

Chairman of the Board of Directors of
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on leave from RWTH Aachen University, Germany

Award Lecture, Nordic Process Control Workshop, Sigtunastiftelsen, August 25, 2016

Content

- **Where do I work?**
- The German "Energiewende":
  objectives and challenges
- Stabilizing the grid by design:
  Managing storage and demand side
- "Intelligent" grid management:
  Demonstrator and research infrastructure
- Control methods and tools:
  Hierarchical and distributed architectures
- Take away messages

JÜLICH
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Major Professional Experiences, since 1992

JÜLICH
FORSCHUNGSZENTRUM

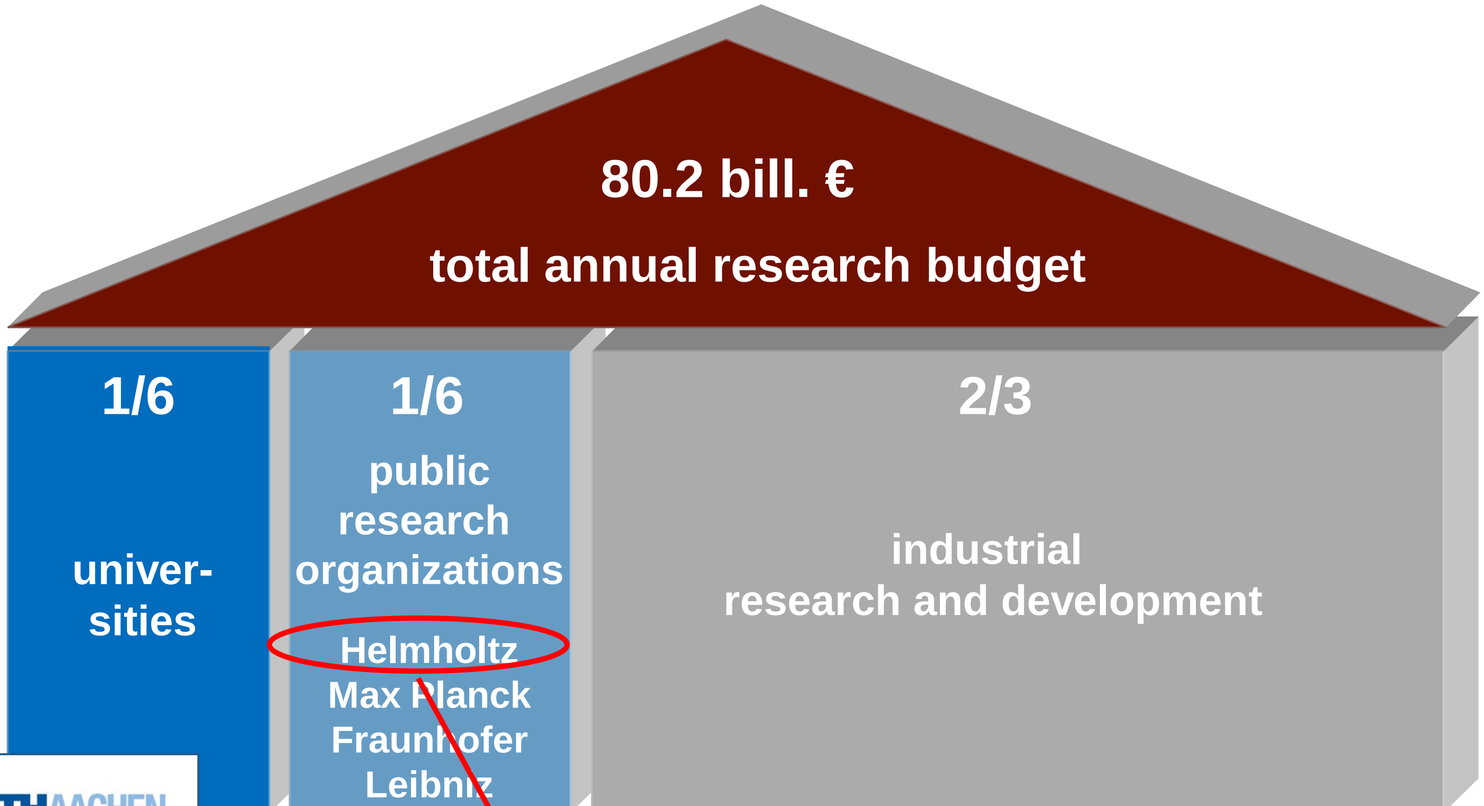
Forschungszentrum Jülich
Chairman of the Board
of Directors & Scientific
Director, since 2014
Research Management

German Council of Science & Humanities
Member & Chairman
2010-2014,
Advisor to the State and
Federal Govermments on
Science Policy

RWTH Aachen University
Professor, Process Systems Engineering, 1992-2014
(Co-)Director, DFG CRC 476 & 540, 1998-2008
Co-Director, AICES & Fuel Design Center, 2008-2011
RWTH Strategy Board, 2007-2011, since 2014
Research, Teaching, Collaborative Research Centers

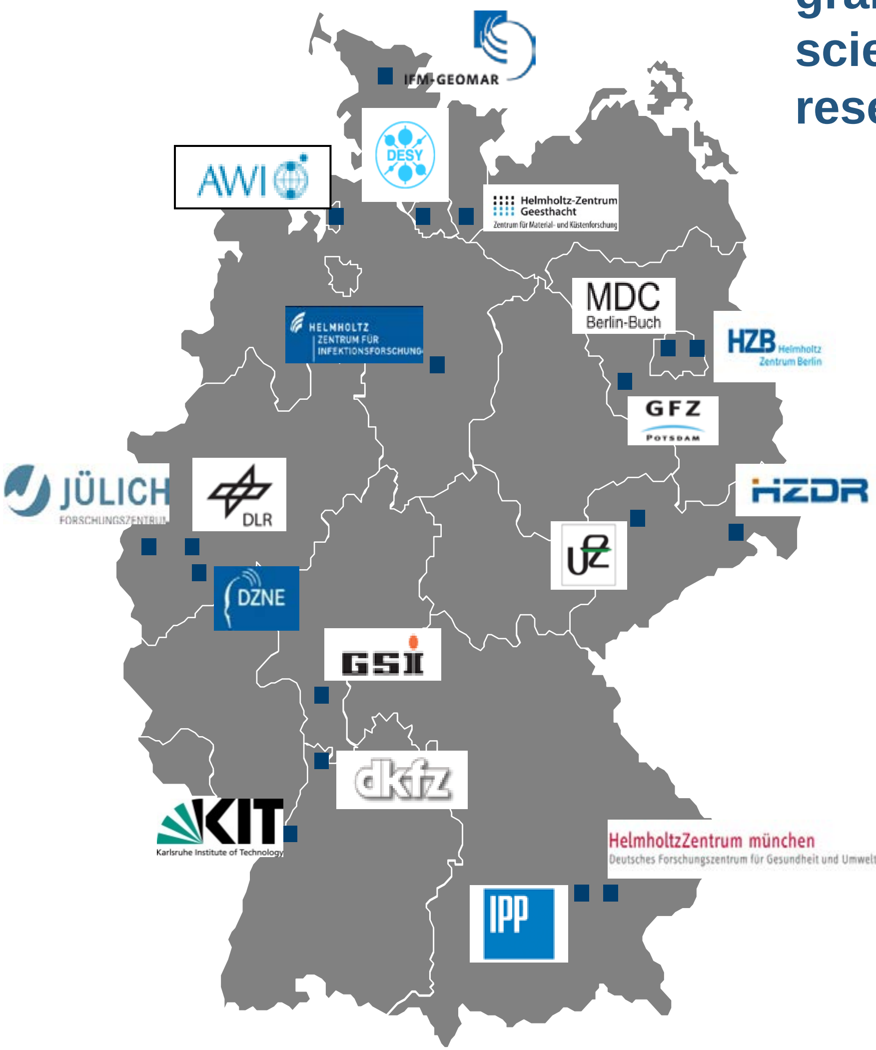
AVT AACHENER VERFAHRENS-TECHNIK

The Big Picture: German Research System

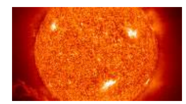


18 centres, 4.24 bill. €
38036 staff
14734 scientists
7446 doctoral students
7476 visiting scientists

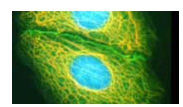
Helmholtz Association

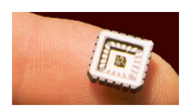


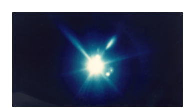
We contribute scientifically to address the grand challenges which face society, science and industry by performing research in strategic programs in


Energy


Earth & Environment

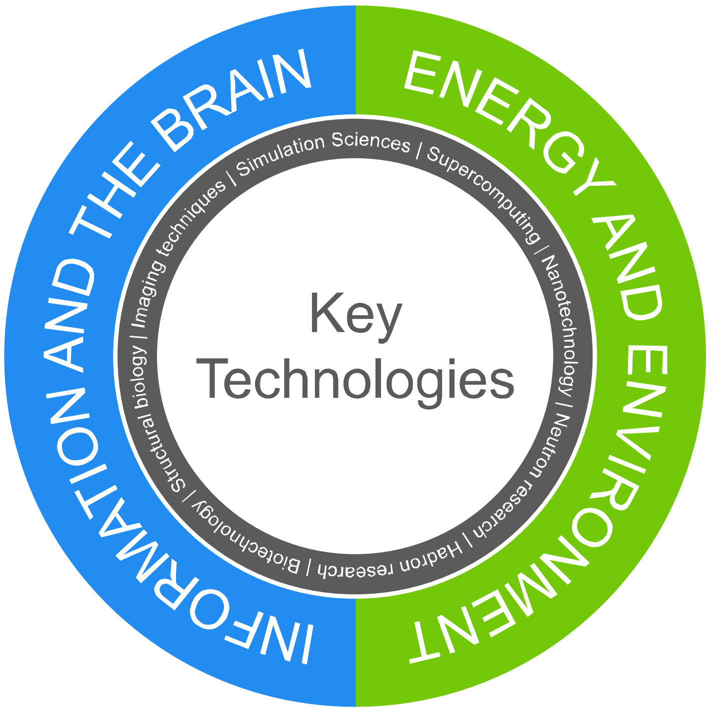

Health


Key Technologies


Matter


Aeronautics, Space and Mobility

Forschungszentrum Jülich – Facts and Figures



Research on **next generation** enabling key technologies

Staff (2015): ~ **5700** employees

Budget (2015): **558 Mio. €**

- Institutional funding: **320 Mio. €**
- Third party funding: **238 Mio. €**

Project administration: **1.6 Billion €**

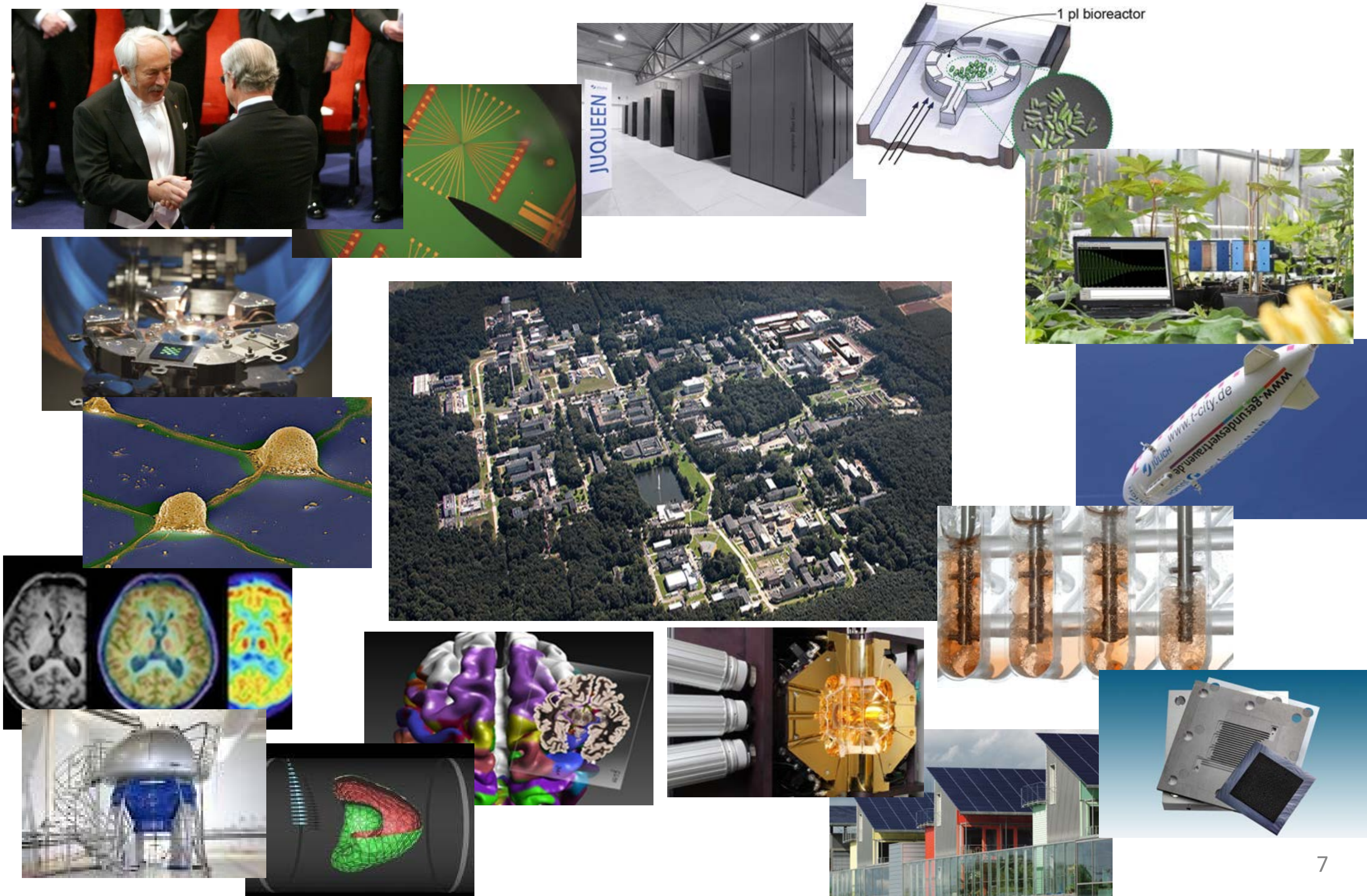
Education:

- ~ 900 Phd students
- ~ 350 Trainees

JARA collaboration

- 6 JARA Sections, 4 JARA Institutes
- ~ 200 PIs involved

Forschungszentrum Jülich – Impressions



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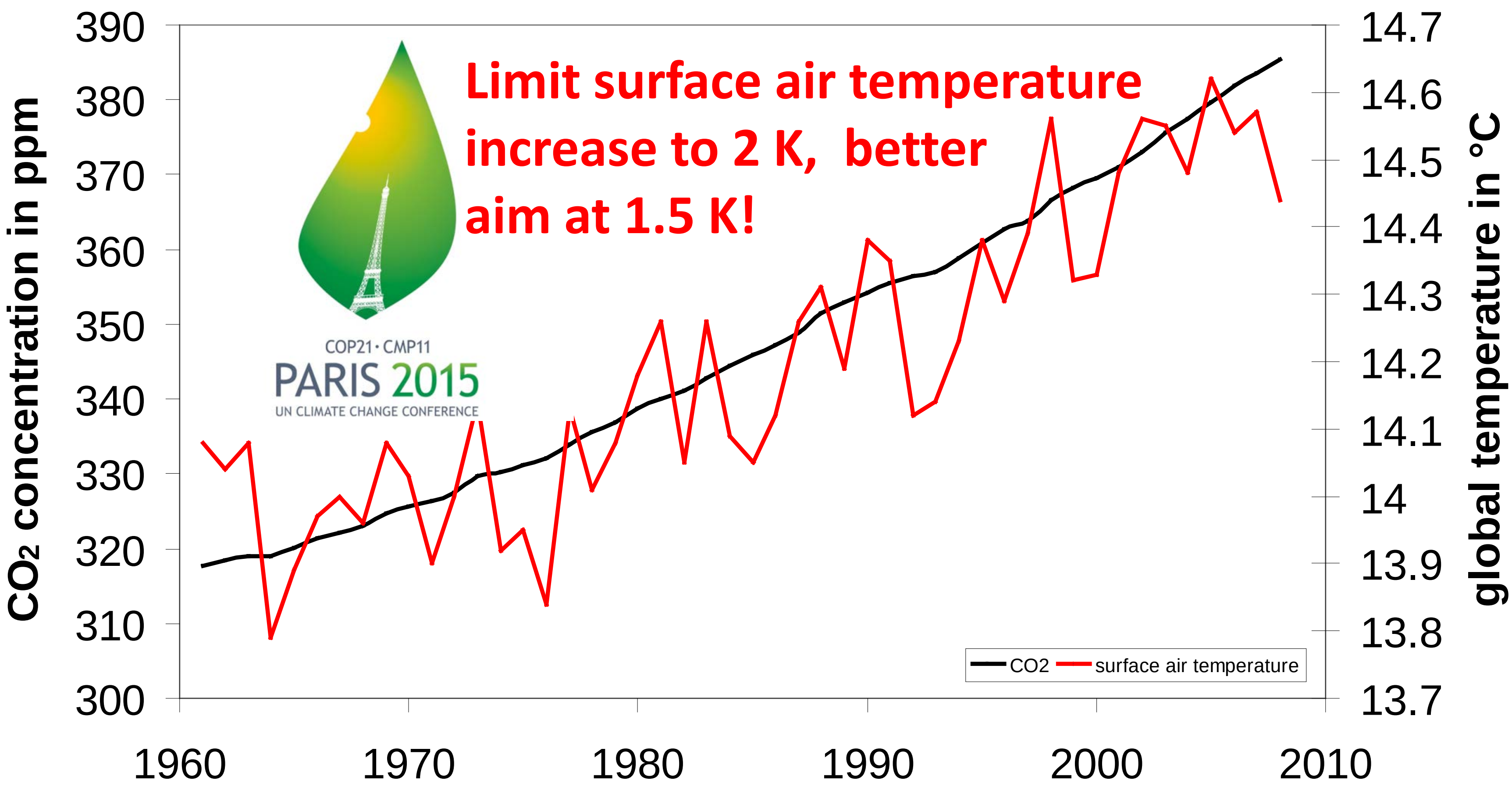
- Take away messages

Source: Siemens Energie-Puzzle

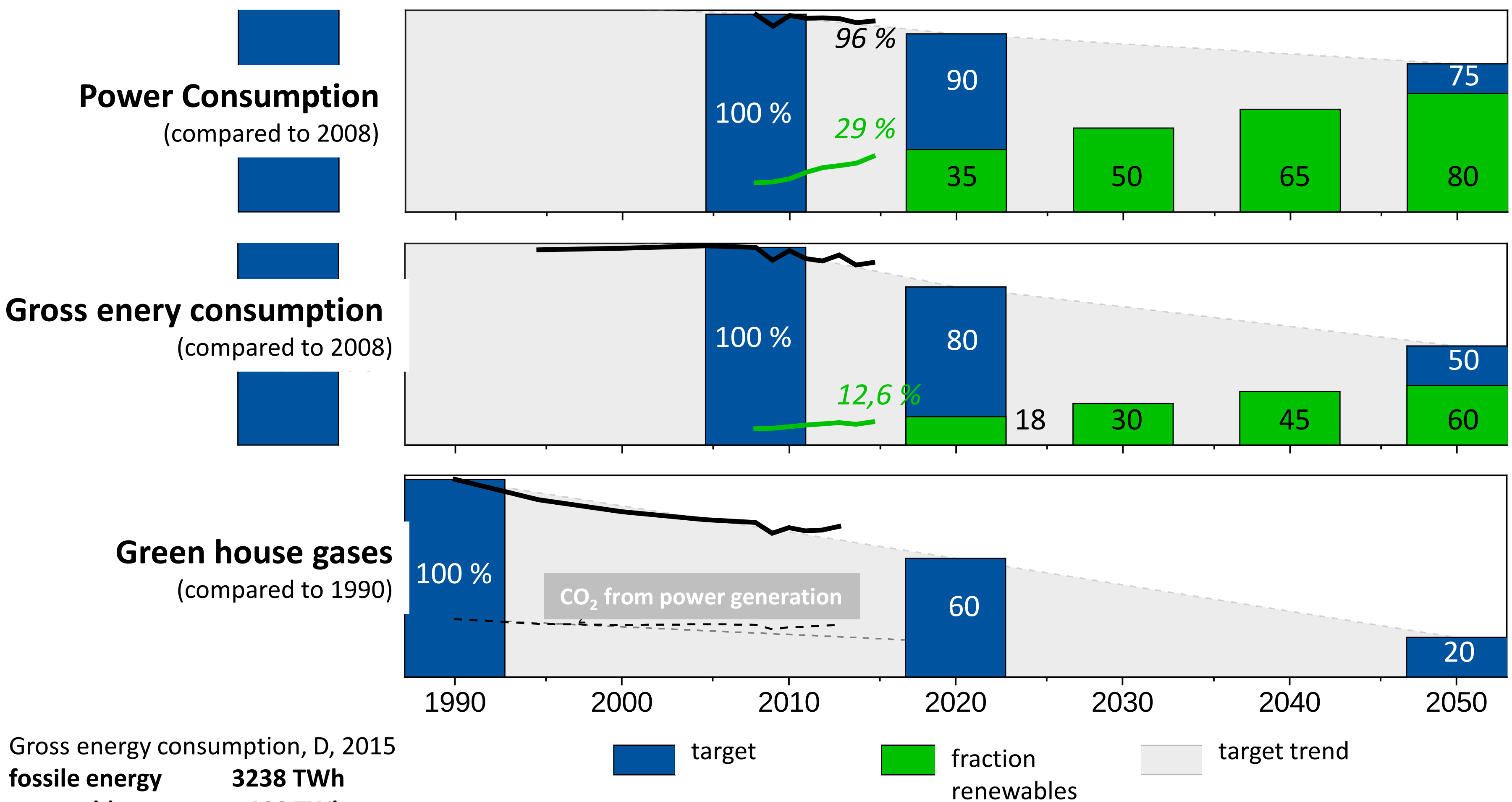
We Face Climate Change!



http://cdn.zmescience.com

Targets for the German Energy System 2050

. . . defined by the German Federal Government



Gross energy consumption, D, 2015

fossile energy **3238 TWh**

renewable energy **466 TWh**

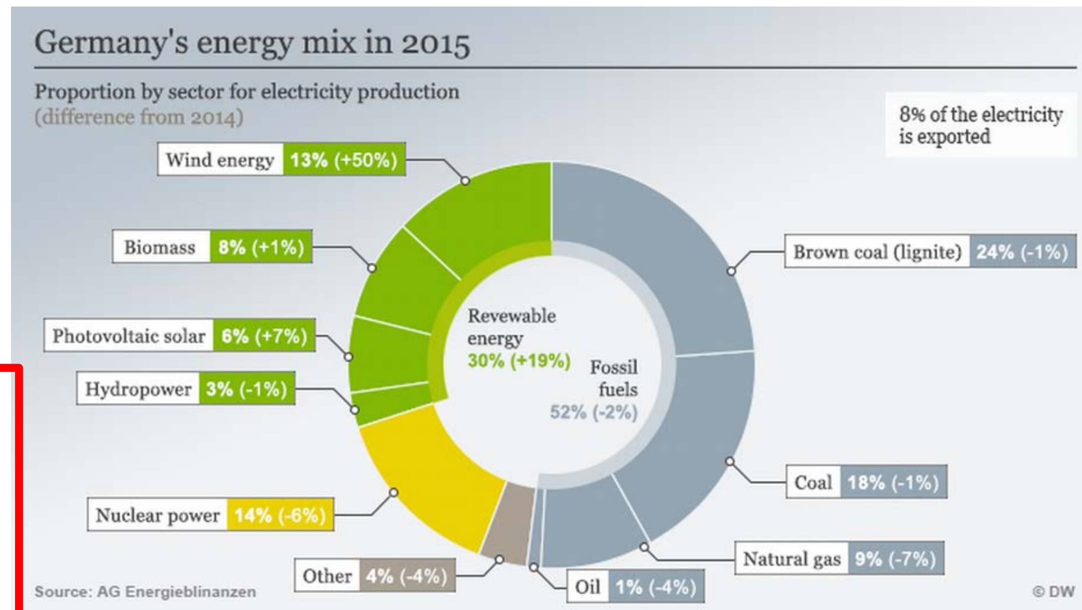
AGEB Jahresberichte 2010-2014
BMWi Energiedaten, Stand Januar 2016

The Current Energy Mix in Germany

Nuclear energy (~14%)
- strong anti-nuclear movement in Germany since 1970s
- Government decision after Fukushima event in 2012: shutdown of all nuclear power plants by 2022

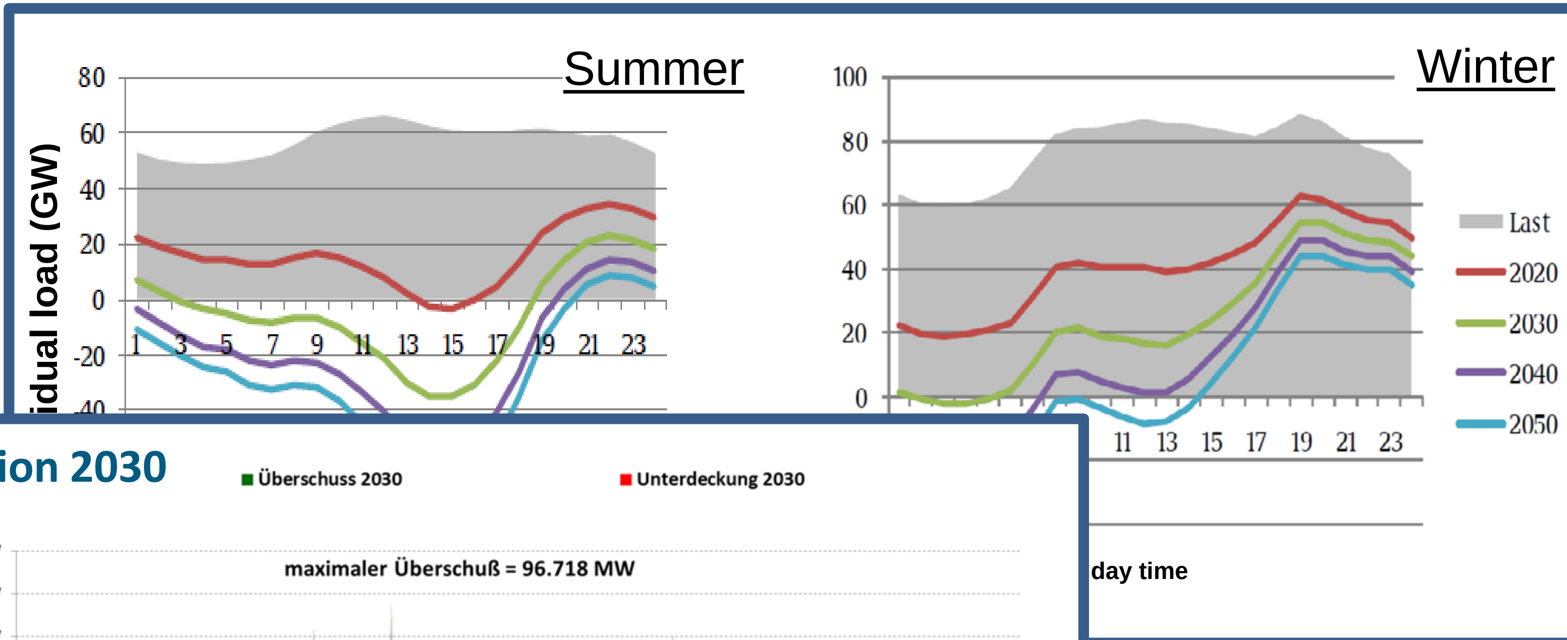
Clean fossil-fired power plants (~52%)
- societal opposition toward carbon capture and storage
- shutdown of all coal-fired power plants by 2040 under discussion

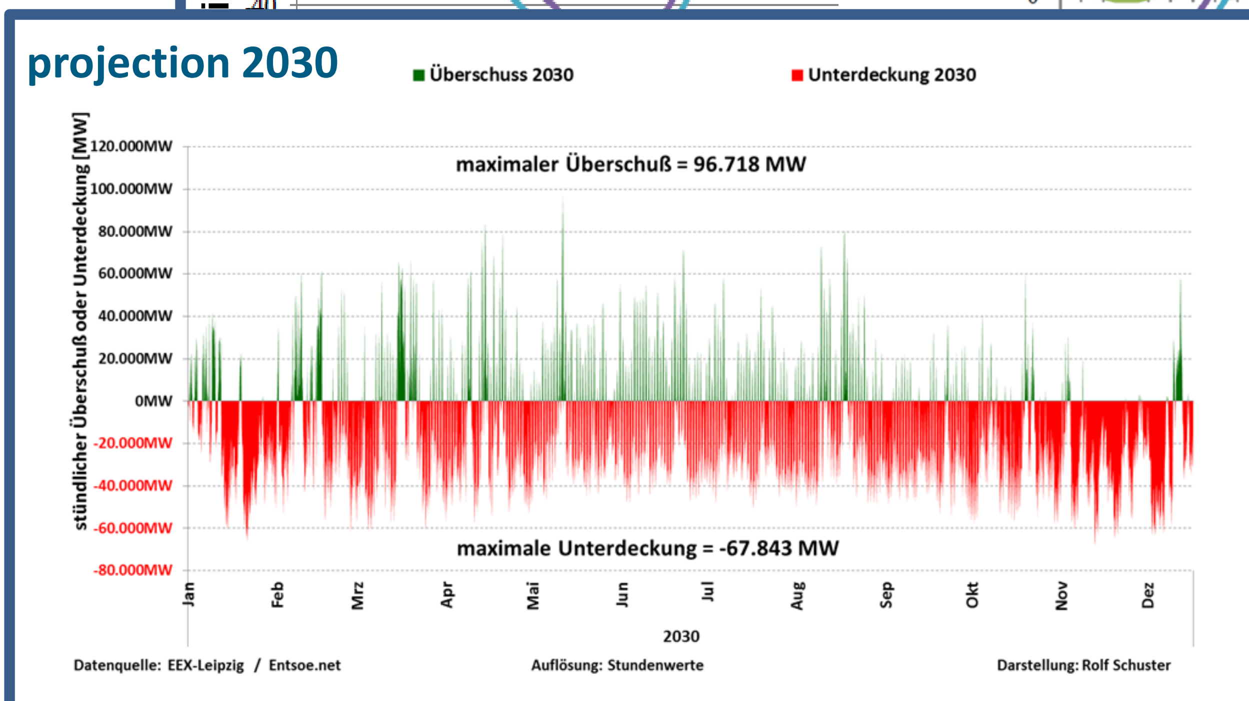
Renewable energies (~30%)
- on-shore and off-shore wind power
- biomass-to-gas
- solar (heat and) power
- hydropower



Energy mix (electricity generation) in Germany (2015)
Source: AG Energiebilanzen

The Challenge: Volatile and Decentralized Generation





Electricity prices, D, 2015

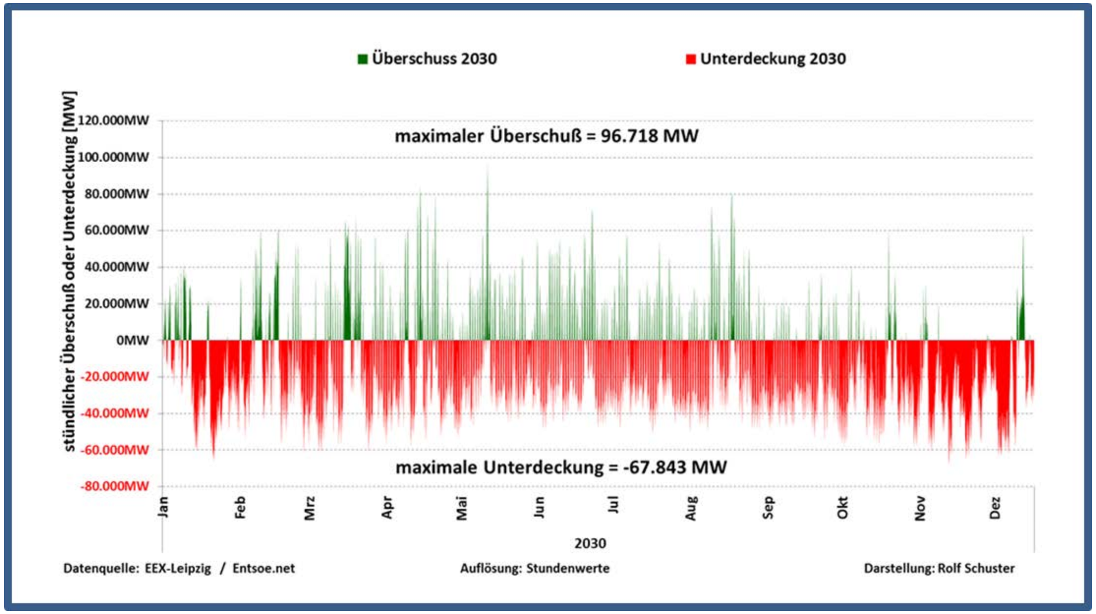
Spot market: 25 €/MWh

Household: 295 €/MWh

Industry: 149 €/MWh

https://www.energy-charts.de/price.htm

The Challenge: Volatile and Decentralized Generation



- new production and distribution technologies and services
- wide-area overhead power grid
- local “capacity reserves” on different scales: power plants vs. storage systems

- flexibilisation and use of overcapacity: supply-driven rather than demand-driven consumption (households, industrial production, …)
- „intelligent“ (i.e., optimal) real-time planning, scheduling / trajectory planning and control of energy supply, storage, and demand
- “smart data“ and „smart models“ for „smart grid solutions“: data-driven and model-based grid management technologies

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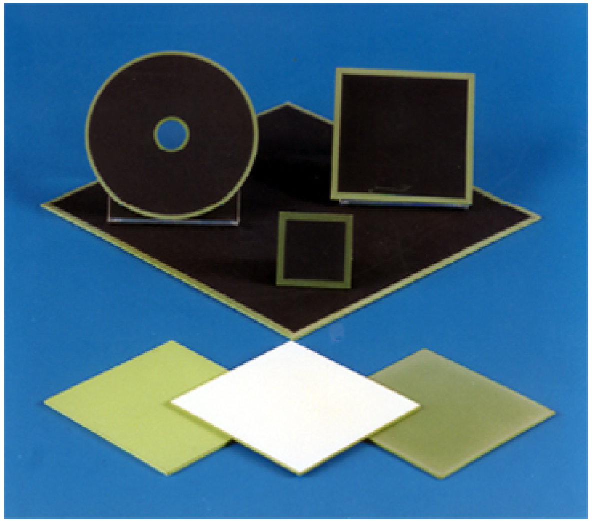
http://mcs.open.ac.uk/energymeeting/energymeeting2015/

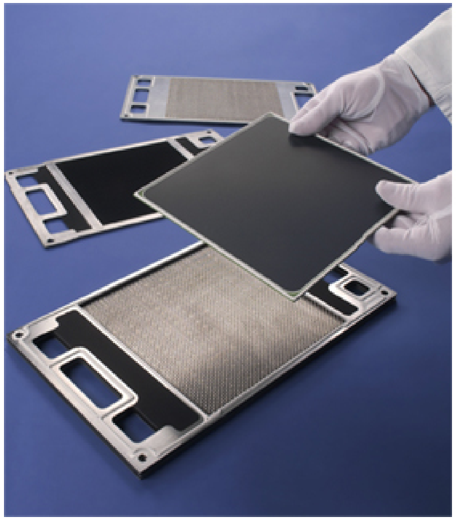
Mitglied der Helmholtz-Gemeinschaft

Key Technology: Reversible Solid-Oxide Fuel Cell

Research@FZJ: Eichel, Guillon, Singheiser, Stolten et al.



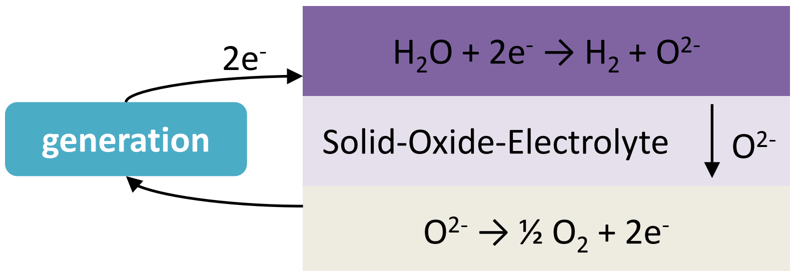
Materials design, synthesis, and processing



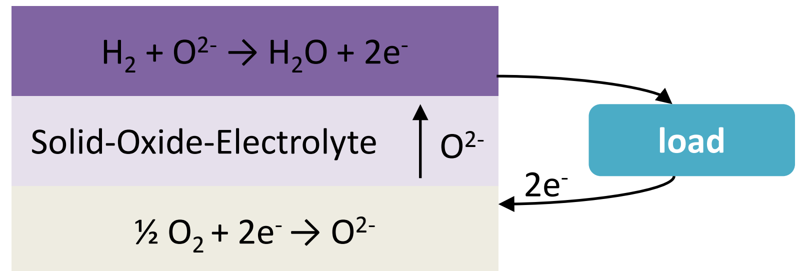
Cell and stack design

Systems design and testing (<100 kW)

Key Technology: Reversible Solid-Oxide Fuel Cell

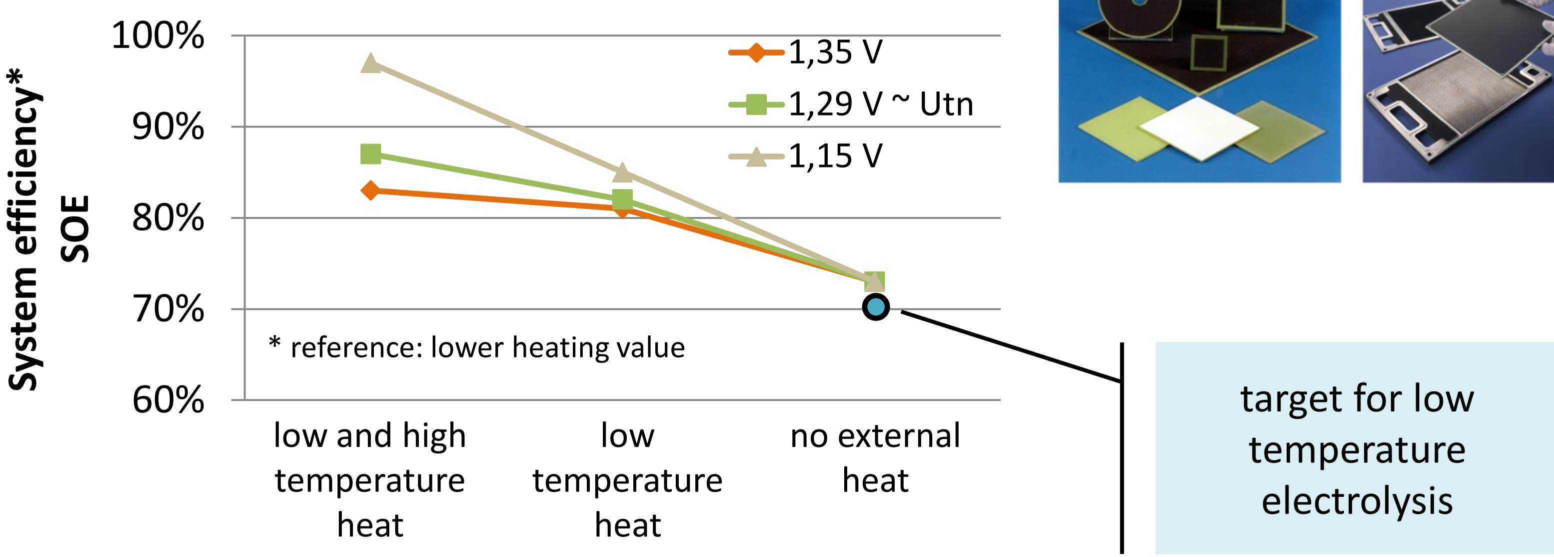


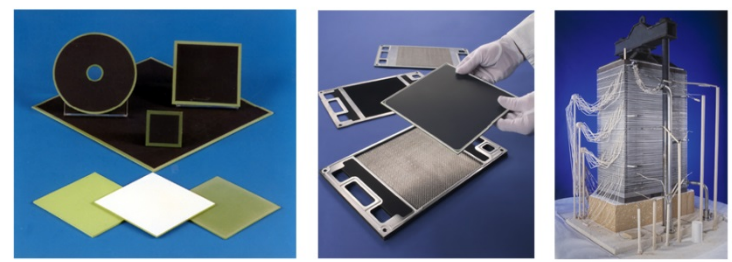
SOE, electrolysis



SOFC, fuel cell

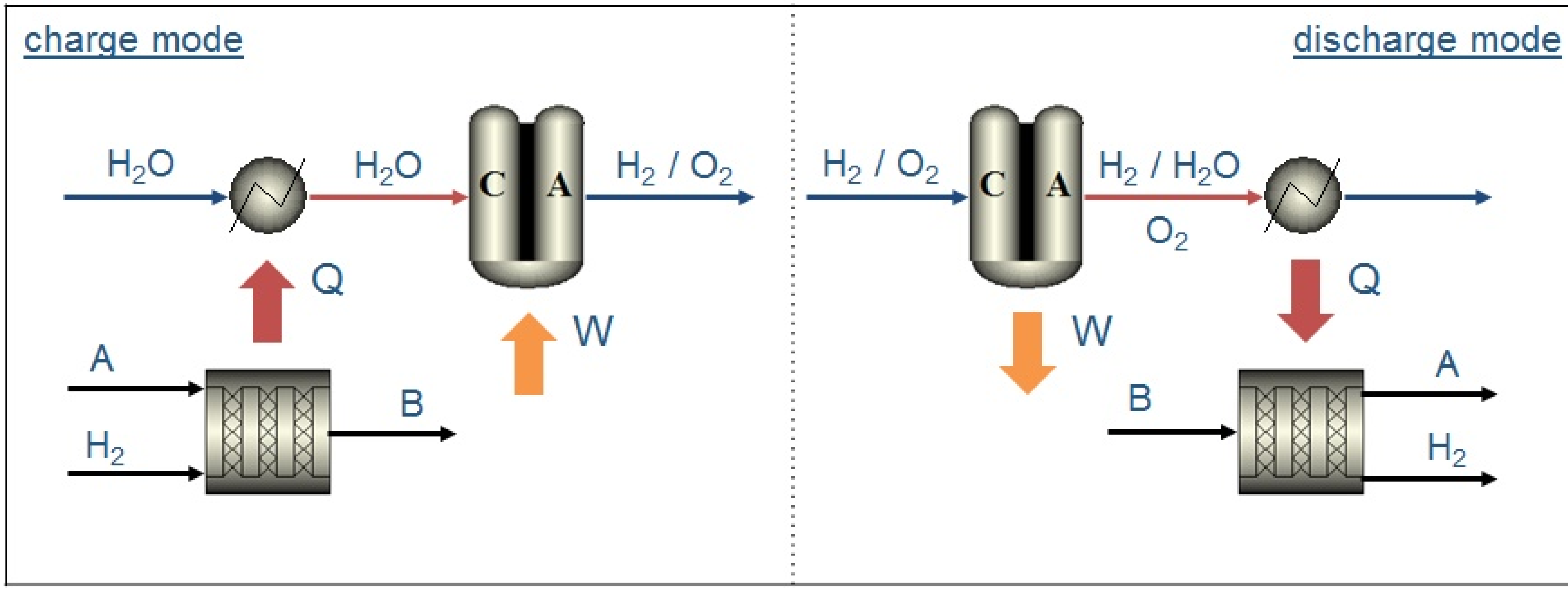
High temperature SO electrolysis





A Novel Concept for Power-to-Chemicals-to-Power

RSOFC integrated with a chemical reaction



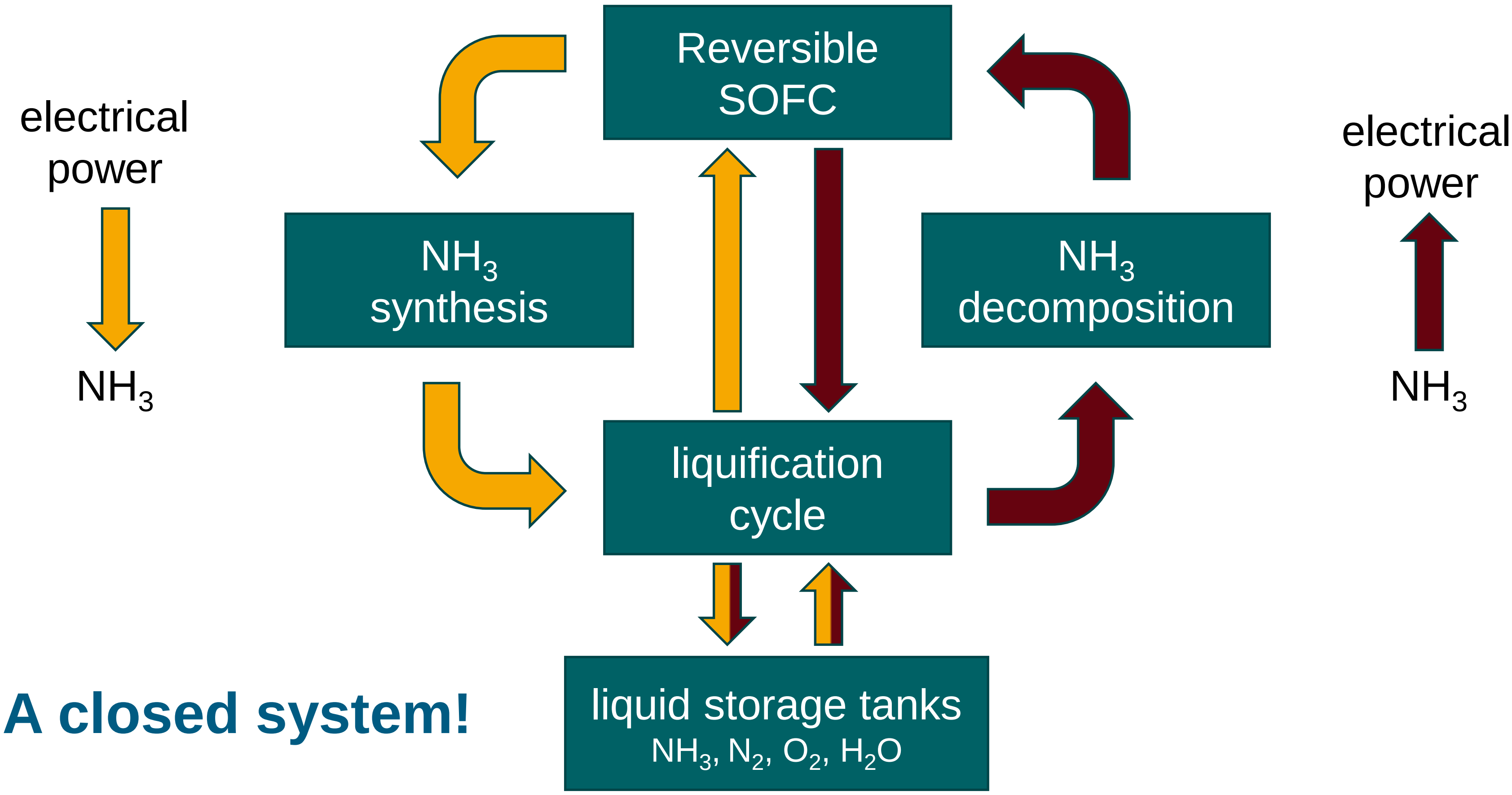
Ammonia – a promising candidate

- storage in large volume, easy to handle
- substrates are water and air (nitrogen)
- no side-products, simple separations

$$N_2 + 3\,H_2 \leftrightarrow 2\,NH_3$$
$$\Delta_R H = -30.8\ \text{kJ/mol}\ H_2$$

Wang, Mitsos, Marquardt (in prep.)

Ammonia-Based Energy Storage System



A closed system!

Wang, Mitsos, Marquardt (sub.)

Ammonia-Based Energy Storage System

Performance for nominal steady-state operation

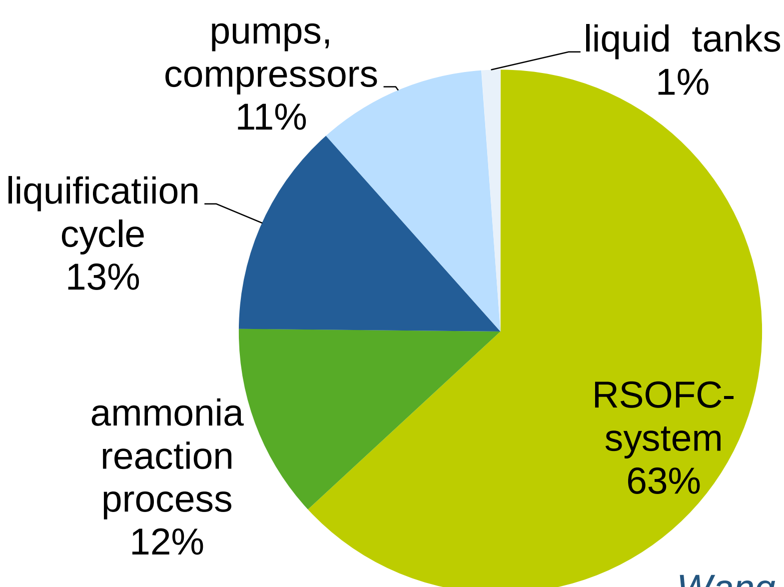
Scenario

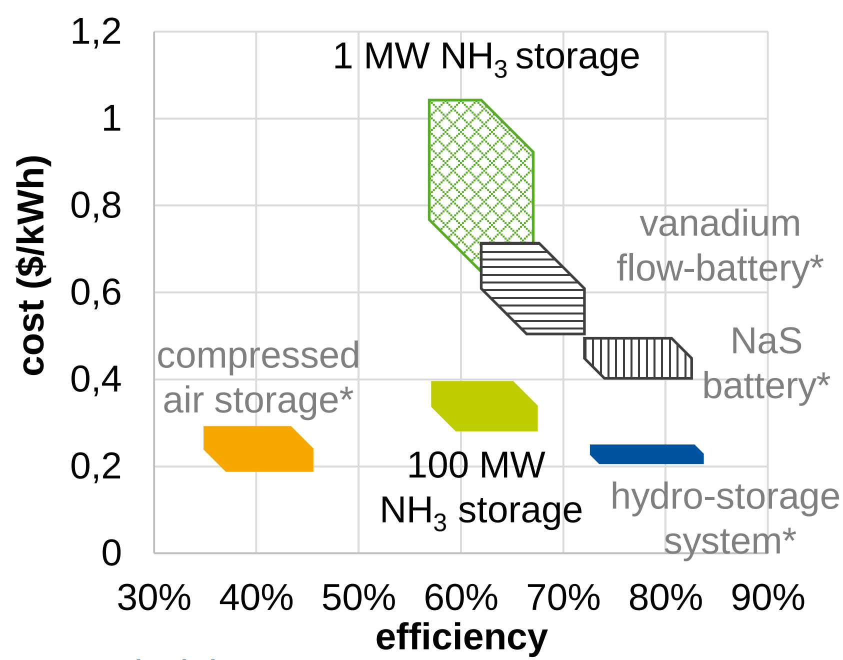
- 100 MW capacity
- 10 h/d charge/discharge time, 4 h/d storage time

Optimization model

- 29.796 vars, 7 decisions

	max. efficiency	min. cost
efficiency (%)	72	64
storage cost ($/kWh)	0,35	0,24

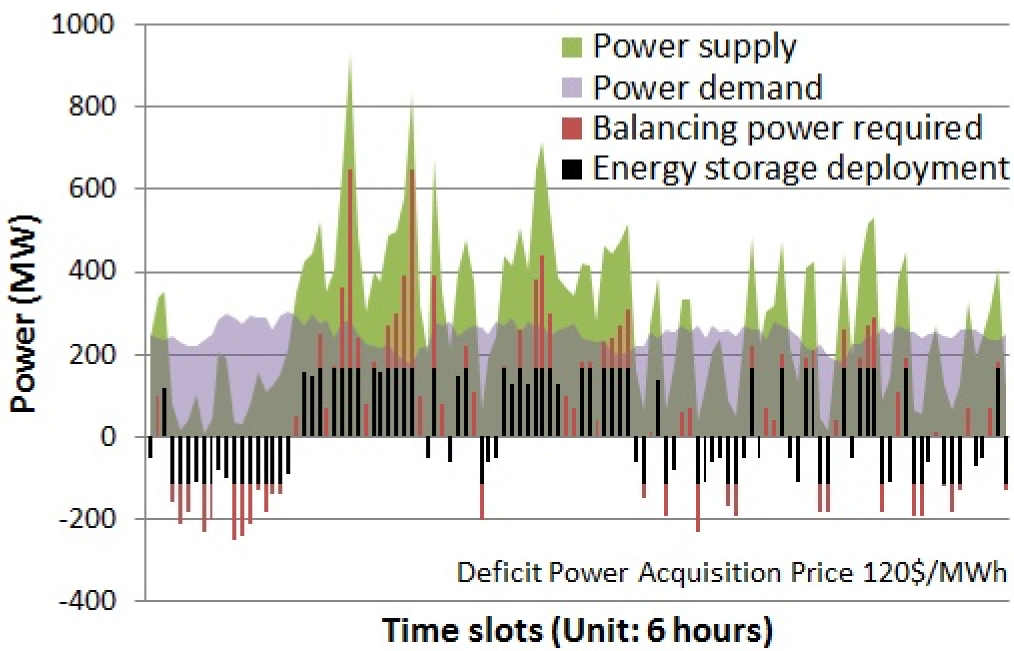




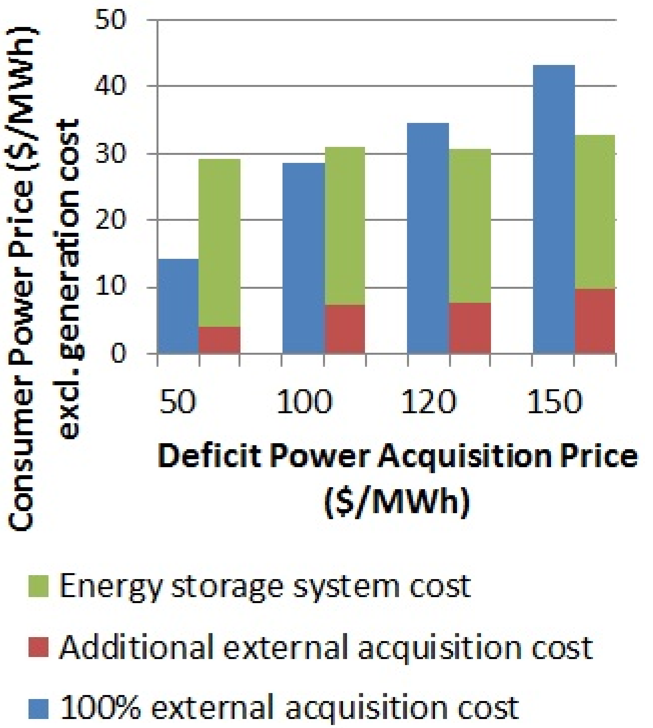
Wang, Mitsos, M. (sub.)

Ammonia-Based Energy Storage System

Performance under transient operation



- Total round-trip efficiency 62% for typical scenario, February, Southern Germany



Comparison of consumer power prices:

- 100% external power acquisition
- using ammonia-based energy storage system

Wang, Mitsos, M. (in prep.)

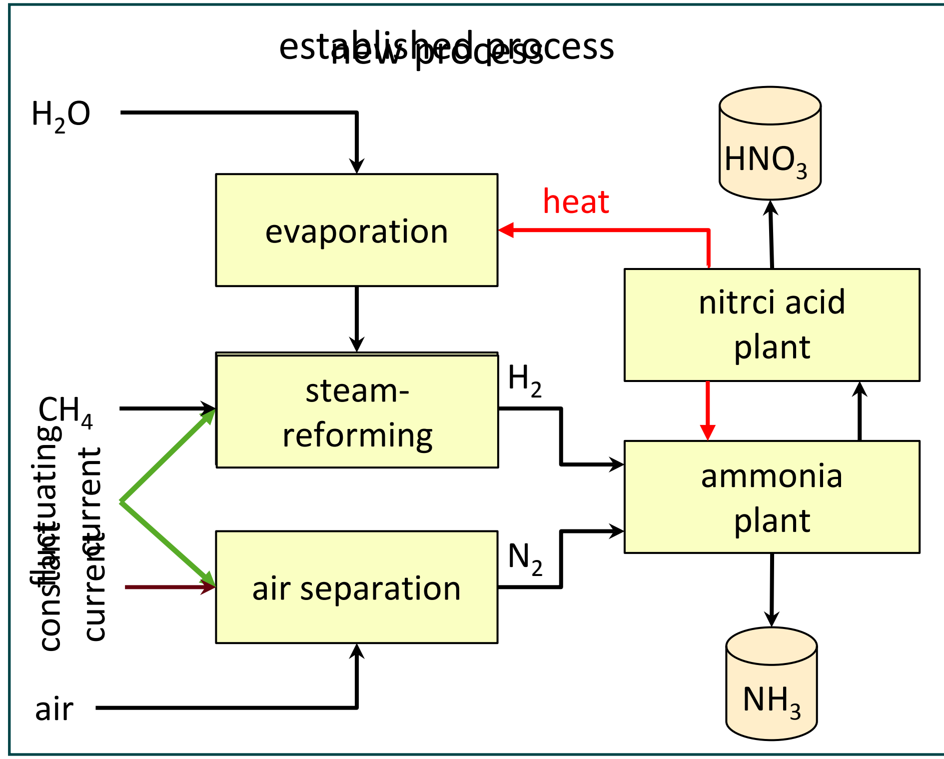
Demand-Side Management – NH_3/HNO_3 Complex

Established ammonia process

- steady-state operation
- H_2 from steam reforming
- high emissions (1,7 t CO_2/t NH_3)

Novel NH_3/HNO_3 complex

- transient operation
- H_2 from electrolysis
- zero CO_2 emission
- heat integration with nitric acid
- highly energy-efficient (7.0 MWh_{el} / t NH_3)

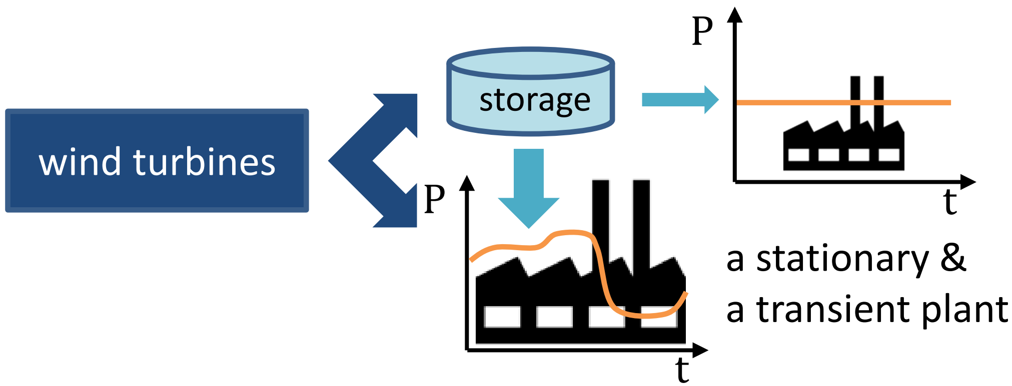


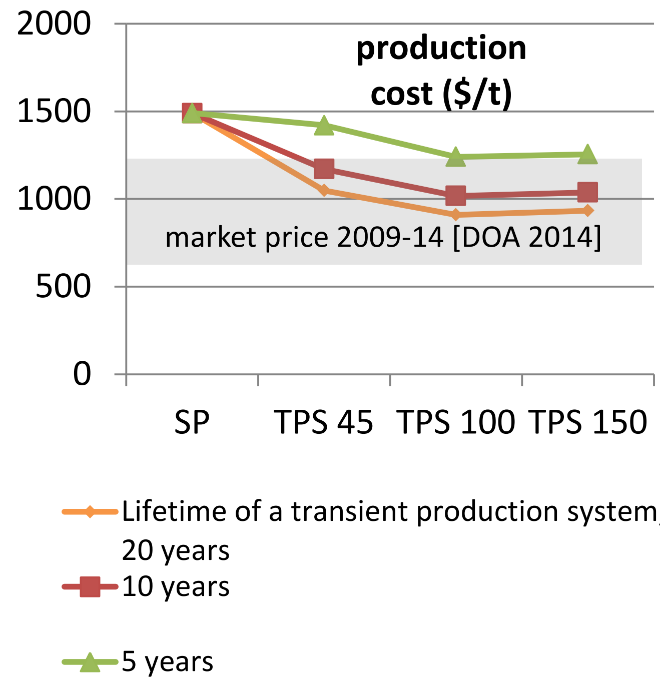
Process design, control and optimization for demand-side management

- economically optimal design for nominal case (stationary operation)
- base layer control (levels, temperatures, product quality
- dynamic real-time optimization for transient load

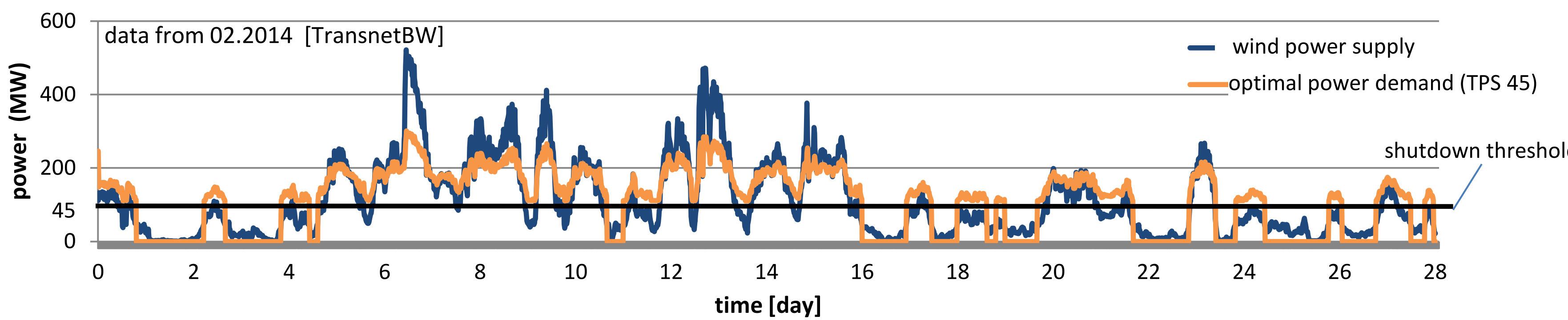
Wang, Mitsos & M. (in prep.)

Demand-side Management: Results





- real power generation scenario
- cost-optimal design
- design variables
  - capacities (storage, both plants)
  - reference load trajectories



Wang, Mitsos & M. (in prep.)

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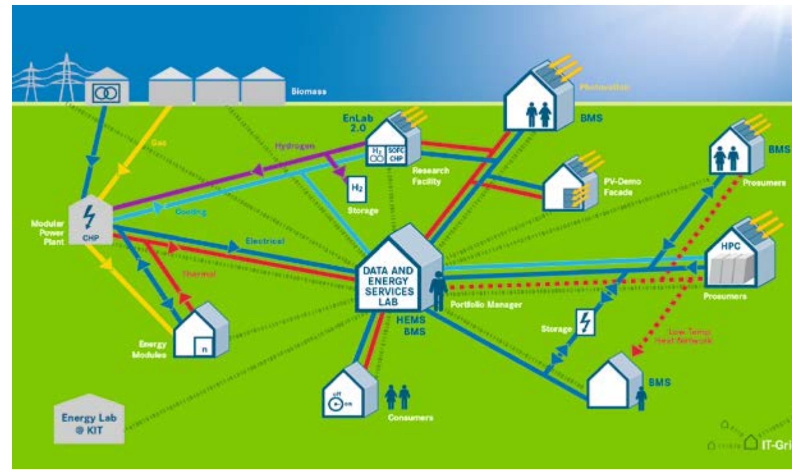

- **“Intelligent” grid management: Demonstrator and research infrastructure**
- Control methods and tools: Hierarchical and distributed architectures
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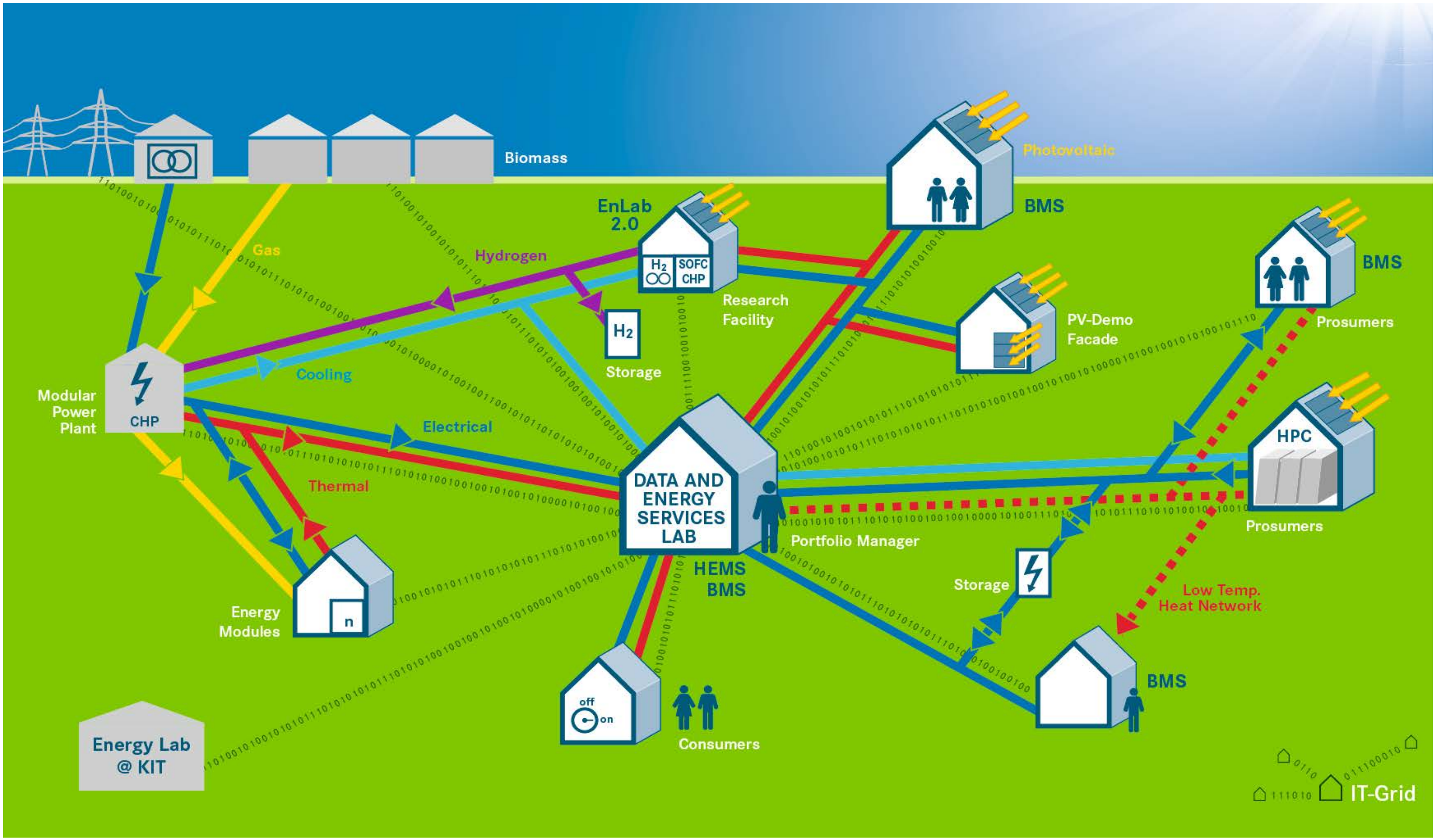
Research for Energy – Energy for Resarch

Living Lab Energy Campus – a Node in a Smart Grid



Living Lab Energy Campus: Overview

Integrated research infrastructure for decentralised urban energy systems

Real-time optimization & control

Integration of energy and info technology components

spatio-temporal sytems dynamics

technology components

data and models:
real time processing
(big) data analytics
simulation & optimization

systems integration: power, heat, storage

user integration and empowerment

Field testing of production and storage technologies at realistic conditions

IT-enabled transition from consumer to prosumer

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The Objective of Operations and Control

Economically optimal operation of transient processes anytime !

market
economic success
Φ

process uncertainties
& disturbances
d

constraints
- environment, equipment, safety
- capacity, quality, reproducability

h

multiple time-scale, spatially distributed model, (O)100 – (O)1.000.000 nonlinear DAEs

Real-time decision making

economic objective, many inequality constraints and time-variant discrete & continuous decisions

manipulated
variables

schedule,
equipment allocation, …

observed
variables

Economic Model-Predictive Control – The Concept

Continuous-time state feedback, moving horizon, no discrete decisions

$$\min_{x,u} \Phi(x,u) \quad s.t.$$

$$\Phi(x,u) = \left\|x(t_f)\right\|_P^2 + \int_{t_0}^{t_f} \|x(t)\|_Q^2 + \|u(t)\|_R^2 dt,$$

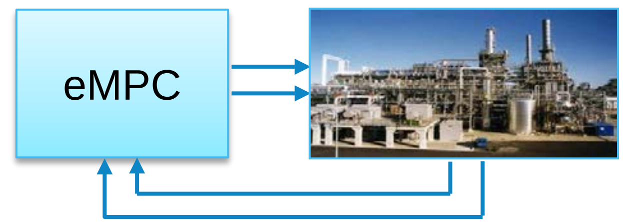
$$\dot{x}(t) = f[x(t),u(t)], \qquad t \in [t_0, t_f],$$

$$x(t_0) = \hat{x}_0,$$

$$x(t) \in X, \qquad t \in [t_0, t_f],$$

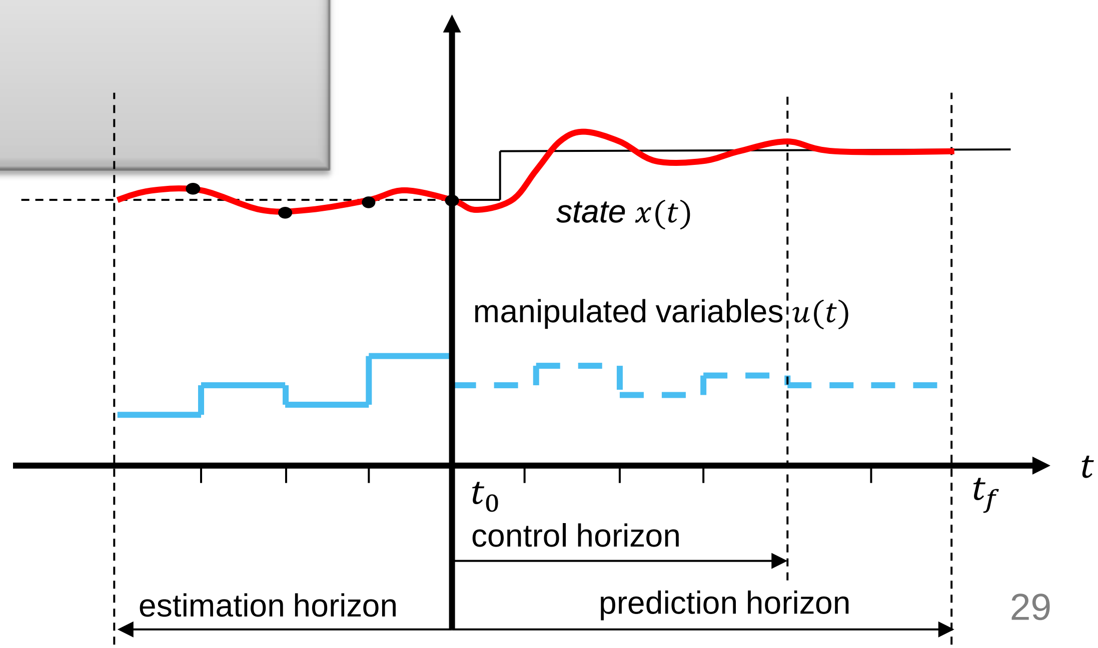
$$u(t) \in U, \qquad t \in [t_0, t_f],$$

$$x(t_f) \in X_f$$



Discretization of manipulated variables:

$$u(t) = \sum_{l=1}^{L} c_l \psi_l(t)$$



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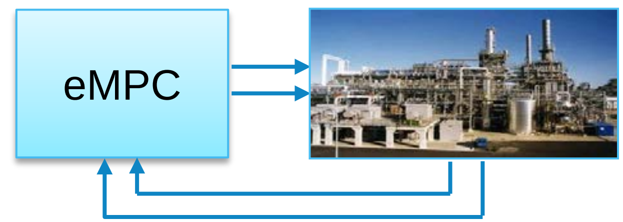


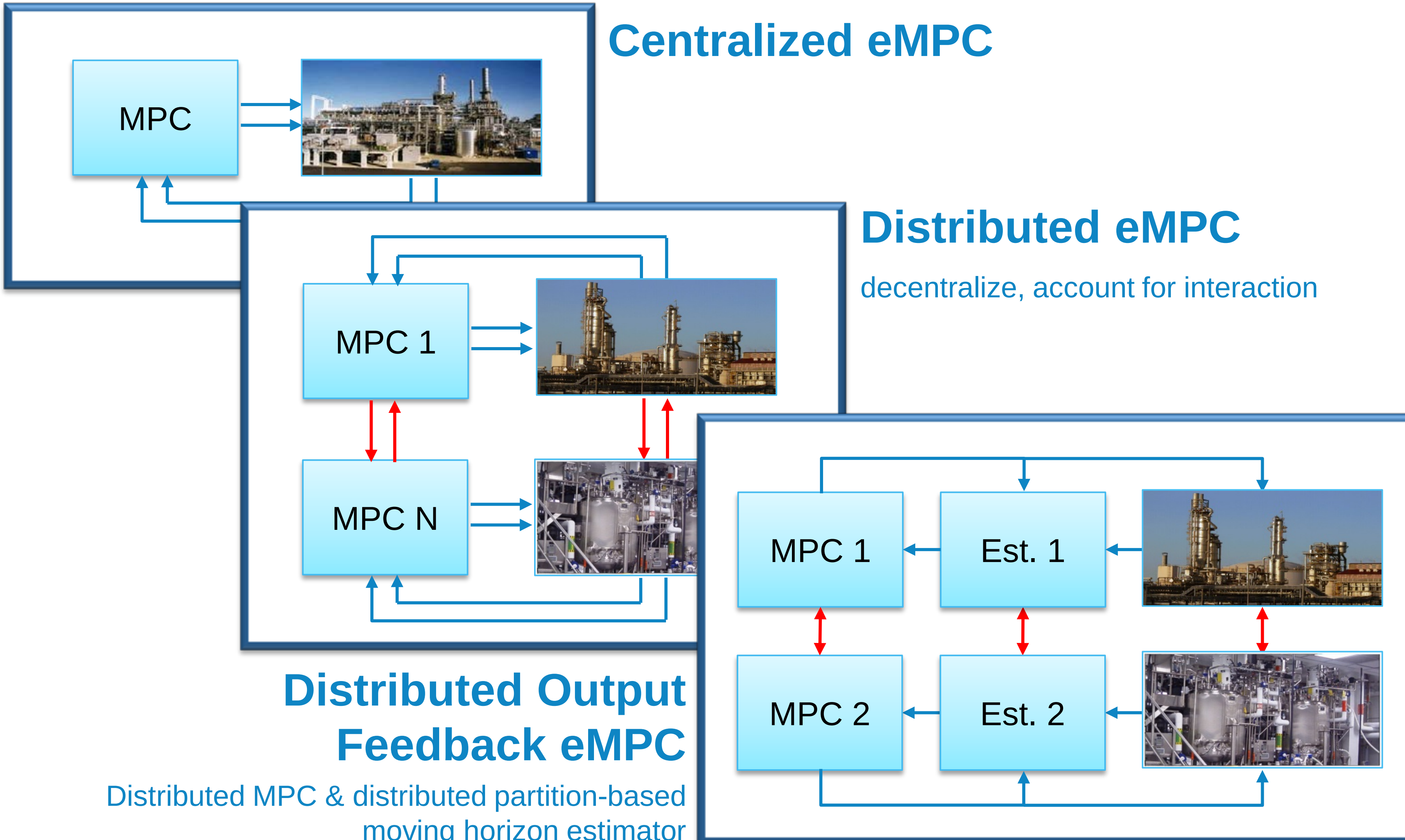
Discretization of manipulated variables:

$$u(t) = \sum_{l=1}^{L} c_l \psi_l(t)$$

Dynamic Real-Time Optimization (DRTO): Gouvea and Odloak (1998), Backx, Bosgra and M. (2000), Helbig, Abel and M. (2000), Kadam et al. (2003), Engell (2007), Kadam, Würth and M. (2007), Würth, Hannemann and M. (2009, 2011), …

Economic Nonlinear Model-Predictive Control (eMPC): Adetola and Guay (2010), Amrit et al. (2011), Diehl et al. (2011), Huang et al. (2012), Grüne (2013), Ellis et al. (2014) …

Decentralization and Distribution



Centralized eMPC

Distributed eMPC

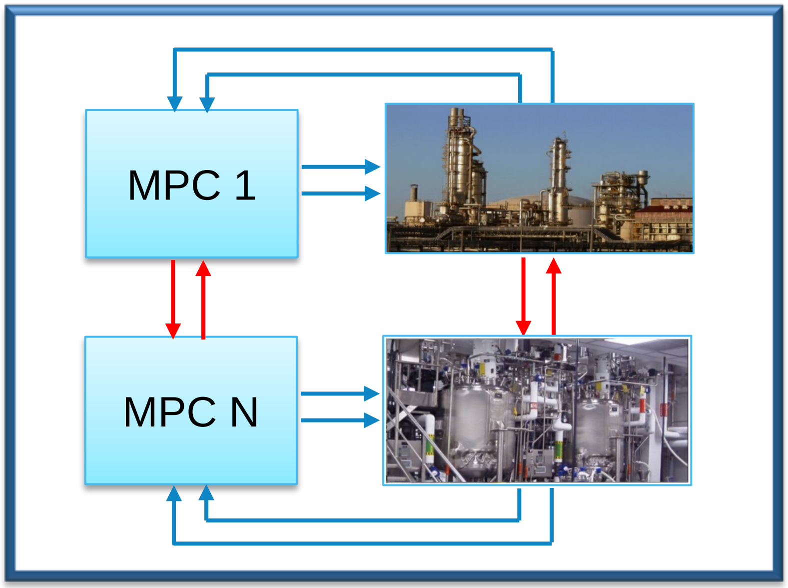
decentralize, account for interaction

Distributed Output Feedback eMPC

Distributed MPC & distributed partition-based moving horizon estimator

Distributed Model-Predictive Control – DMPC

Review on architectures: Scattolini, 2009, Farina et al., 2010
Classic approach – Dual decomposition: Lasdon, 1970, Negenborn et al., 2008, …



Distributed MPC

decentralize, account for interaction

Challenges

- **broad applicability**
- **optimality**
- **convergence**
- **stability**
- **efficiency**

Recent approach – Sensitivity-driven S-DMPC: Mesarovic et.al, 1970, Scheu & M., 2011
Benchmarking of S-DMPC: Alavarado et al., 2011, Maestre et al. 2015

Sensitivity-based Decomposition – DMPC

Continuous-time OCP

$$\min_{x,u} \frac{1}{2}\int_{t_0}^{t_f} \left(\|x(t)\|_Q^2 + \|u(t)\|_R^2\right) dt,$$
$$\text{s.t.} \;\; \dot{x}(t) = Ax(t) + Bu(t), \qquad t \in (t_0, t_f],$$
$$x(t_0) = x_0,$$
$$x \in X, \qquad u \in U$$

Transcription

QP

$$\min_z = \sum_{i=1}^{N} \Phi_i(z) = \sum_{i=1}^{N} \frac{1}{2} z' H_i z + f_i' z$$
$$\text{s.t. } 0 \le c_i(z) = A_i z + b_i, \forall i$$

S-DMPC

- optimality ✓
- convergence ✓
- stability
- efficiency ✓

Parallel iterative solution using decomposed subproblems

iterations

$$\min_{z_i} \Phi_i^*(z)$$
$$\Phi_i^*(z) = \Phi_i(z) + \left[\sum_{j=1, j\neq i}^{N} \left.\frac{d\Phi_j}{dz_i}\right|_{z^{[k]}}^{T} - \lambda_j^{[k]T} \left.\frac{d\, c_j}{dz_i}\right|_{z^{[k]}} \right] \left(z_i - z_i^{[k]}\right)$$
$$\text{s.t. } c_i(z) \ge 0,$$

Theory for **linear** systems, benchmarking with **(simple)** nonlinear plants: Scheu & M., 2011; Alavarado et al., 2011, Maestre et al. 2015

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Distributed State Estimation

Classic approaches to state estimation

Centralized eMPC

- **Kalman Filter** (Kalman, 1960, Hassan et al., 1978, Venkat et al., 2006, Roshany-Yamchi et al. 2013)
- **Luenberger Observer** (Luenberger, 1964, Venkat et al. 2005, Farina & Scattolini, 2011, Giselsson, 2013)

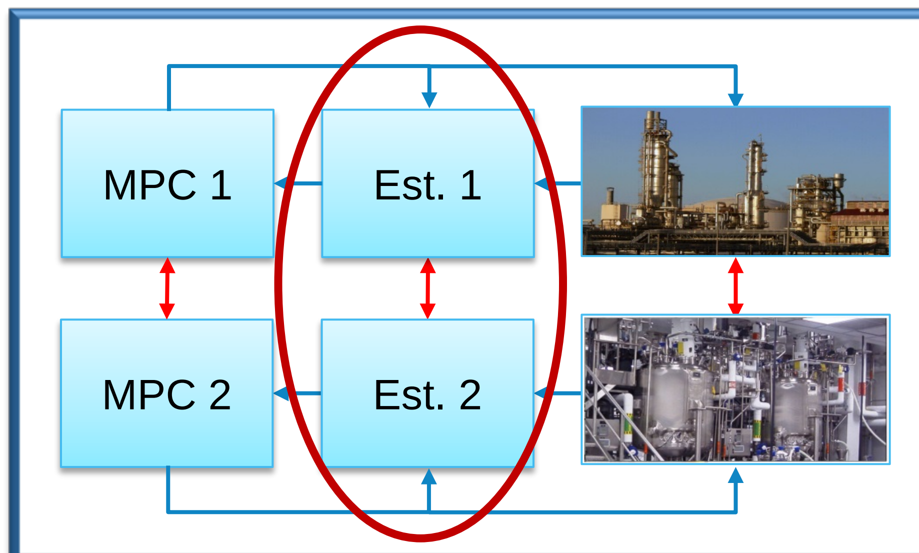
More recent approach

- **Moving horizon estimation** (Grizzle & Moraal, 1990, Michalska & Mayne, 1992)
  Partition-based estimation (Farina et al., 2011, Schneider et al. 2013, 2014, 2015, 2016)

iterative & inherently parallel algorithm with optimal performance of centralized estimator

Distributed Output Feedback eMPC

Distributed MPC & distributed partition-based moving horizon estimator



Sensitivity-based Decomposition – PMHE

Discrete-time moving horizon estimation problem

$$\min_{\Delta x(k^0),\{x\},\{w\},\{v\}} \frac{1}{2}\left(\|\Delta x(k^0)\|^2_{\tilde{P}} + \sum_{k=k^0}^{k'-1} \|\mathrm{w}(k)\|^2_{\tilde{Q}} + \sum_{k=k^0}^{k'} \|v(k)\|^2_{\tilde{R}} \right)$$

$$\begin{aligned} \text{s.t. } x(k^0) &= \bar{x}(k^0) + \Delta x(k^0), \\ x(k+1) &= Ax(k) + w(k), \\ y(k) &= Cx(k) + v(k) \end{aligned}$$

QP

$$\min_{z} \sum_{i=1}^{N} \Phi_i(z),$$

$$\text{s.t. } c_i(z) \geq 0, \quad \forall i$$

Parallel iterative solution using decomposed subproblems

iterations

$$\min_{z_i} \Phi_i^*(z)$$

$$\Phi_i^*(z) = \Phi_i(z) + \left[\sum_{j=1, j\neq i}^{N} \frac{d\Phi_j}{dz_i}\bigg|_{z^{[k]}}^{T} - \lambda_j^{[k]^T} \frac{d\, c_j}{dz_i}\bigg|_{z^{[k]}} \right] \left(z_i - z_i^{[k]}\right)$$

$$\text{s.t. } c_i(z) \geq 0,$$

R-PMHE

- **optimality**
- **convergence** ✓
- **stability** ✓
- **efficiency** ✓

Theory for **linear** systems, various formulations with different and theoretical properties, benchmarking with (non-)linear plants: Schneider et al. 2013, 2014, 2015, 2016

Distributed Output Feedback MPC

Established approaches

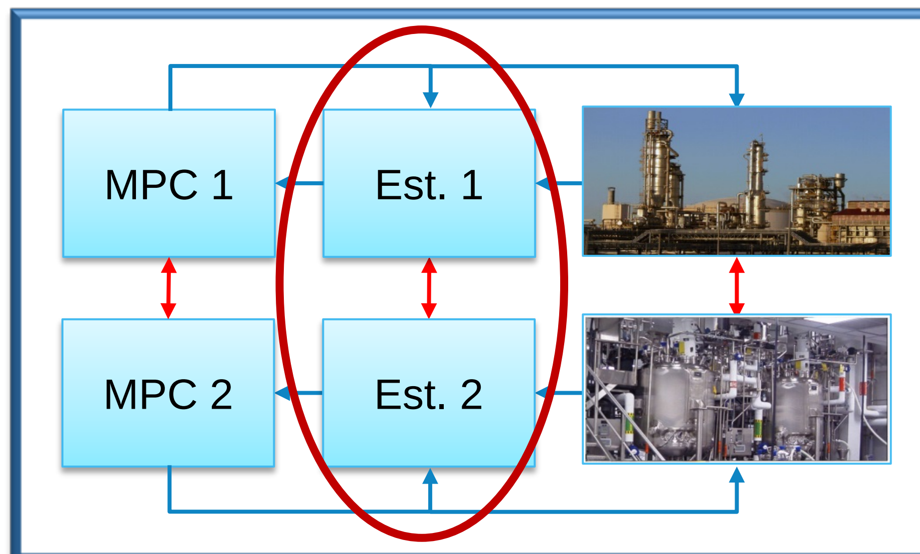
- **DMPC & centralized state estimation** (Zheng et al., 2009, Hu & El-Farra, 2013)
- **DMPC & distributed Luenberger observer** (Venkat et al., 2005, …)
- **DMPC & distributed Kalman filter** (Venkat 2006 et al., …)

Novel approach

- **S-DMPC & R-PMHE**
  (Schneider, Scheu & M., 2014)
- **Alkylation plant case study:**
  130 nonlinear DAEs, 25 states,
  5 controls, 6 measurements, linear
  S-DMPC & R-PMHE, 1 iteration

Distributed Output Feedback MPC

Distributed MPC & distributed partition-based moving horizon estimator



Distributed Output Feedback MPC

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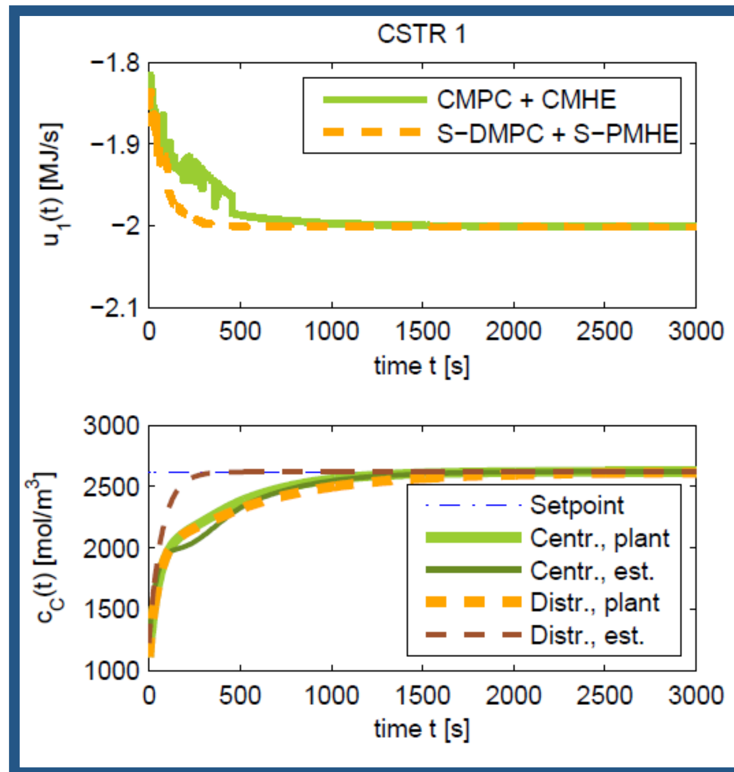


Many open issues

- Formulations, decomposition, and theoretical properties (stability …)
- Efficient numerical algorithms
- Real-world (nonlinear) applications
- Distributed output feedback eMPC

Economic Model-Predictive Control – Revisited

Continuous-time state feedback on moving horizon

$$\min_{x,u} \Phi(x,u) \qquad s.t.$$

$$\Phi(x,u) = \left\|x(t_f)\right\|_P^2 + \int_{t_0}^{t_f} \|x(t)\|_Q^2 + \|u(t)\|_R^2 dt,$$

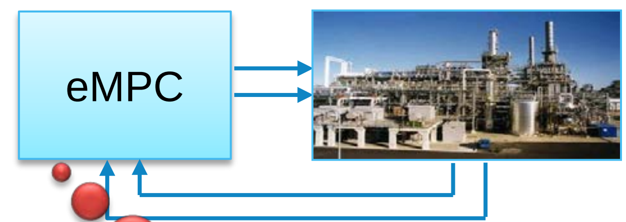
$$\dot{x}(t) = f[x(t), u(t), d(t)], \qquad t \in [t_0, t_f],$$

$$x(t_0) = \hat{x}_0,$$

$$x(t) \in X, \qquad t \in [t_0, t_f],$$

$$u(t) \in U, d(t) \in D, \qquad t \in [t_0, t_f],$$

$$x(t_f) \in X_f$$



Efficient real-time algorithms, fast updates of pNLP by pQP
(Wolf & M., 2016)

$$u_h(t) = \sum_{\kappa=1}^{K_h} (z_\kappa)_h \Psi_\kappa(t) \longrightarrow z_h = \left[(z_1)_h{}^T, \ldots\right]^T$$

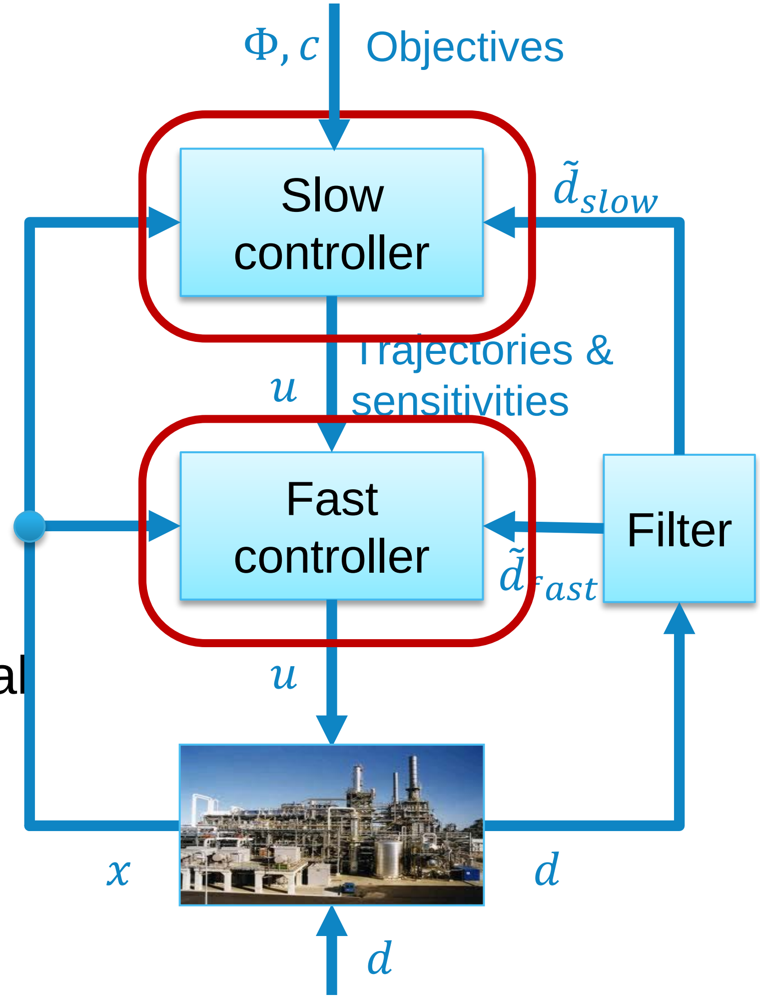
$$d_h(t) \approx \sum_{\kappa=1}^{K_h} \left(\bar{d}_\kappa\right)_h \Psi_\kappa(t) \longrightarrow p_h = \left[\left(\bar{d}_1\right)_h{}^T, \ldots, x_h^0{}^T\right]^T$$

$$\boxed{\begin{array}{l} \min_{z_h} \Phi(z_h, p_h) \\ s.t. \;\; c(z_h, p_h) \leq 0 \end{array}}$$

Parameterization and transcription to pNLP

Hierarchical Two-Layer Architecture for eMPC

- Slow economic nonlinear model-predictive control (NMPC) for trajectory generation
  - Low sampling rate
  - Efficient, robust OC algorithm
- Fast economic NMPC for tracking control and disturbance rejection
  - High sampling rate
  - Initial value embedding / suboptimal / neigboring extremal update (NEU algorithm)



Neighboring Extremal Update (NEU)

- Exploit sensitivity information of previous upper layer NLP solution (*) to generate a fast approximation z_h of the optimal update.

(Kadam & M., 2004, Würth et al., 2009, 2011, Wolf & M., 2016)

- Parametric quadratic programming problem (pQP):

$$\min_{\Delta z_h} \; J(\Delta z_h) \overset{\text{def}}{=} 0.5\, \Delta z_h^T\, L_{zz}^* \Delta z_h + \Delta p_h^T\, L_{pz}^* \Delta z_h + \Phi_z^* \Delta z_h$$
$$s.t. \;\; \mathbf{c}(\Delta z_h) \overset{\text{def}}{=} c^* + c_z^* \Delta z_h + c_p^* \Delta p_h \leq 0$$

Handles changes of active set!
(Ganesh & Biegler, 1987)

L: Lagrange function
c: constraints

p: parameter vector
z: control parameter vector

Tracks necessary conditions of optimality rather than outdated reference trajectory and guarantees consistency between layers!

Optimal solution
$z^*(p^*)$

Φ_z^*, c_z^*, c_p^*
L_{zz}^*, L_{pz}^*

Feedback
$\Delta p_h := p_h - p^*$

NEU
$\Delta z_h := z_h - z^*$

Hierarchical Two-Layer Architecture for eMPC

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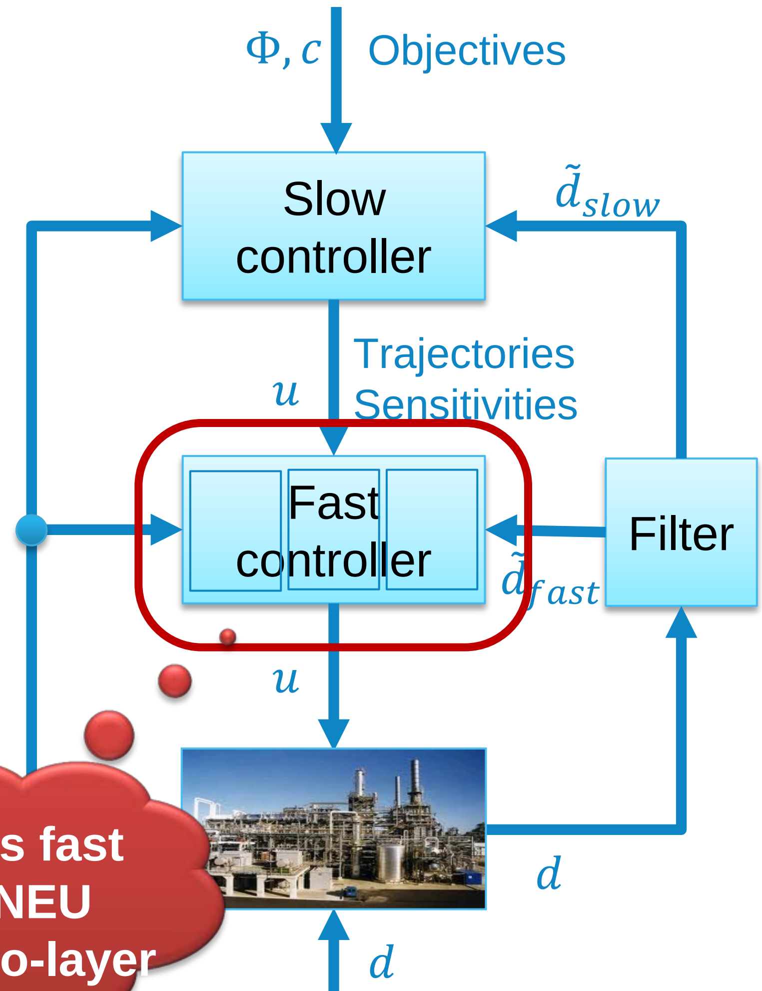
  - High sample rate
  - Initial value embedding / suboptimal / neigboring extremal update (NEU algorithm)
- Distributed fast MPC for systems

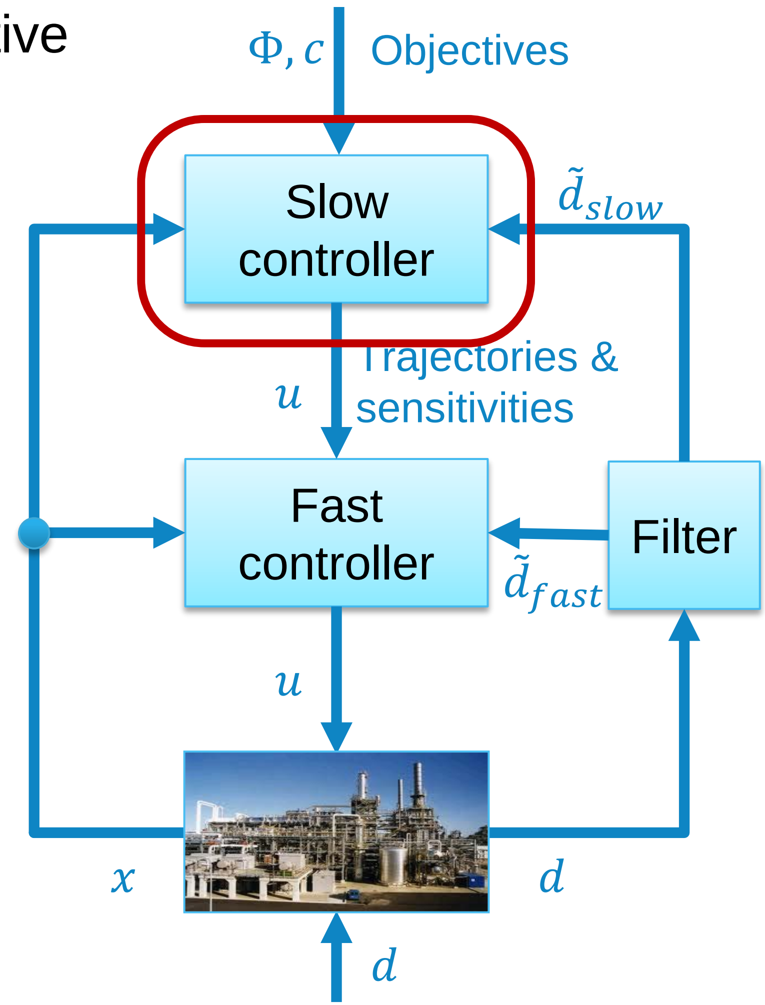
(Wolf et al., 2012)



Use S-DMPC as fast controller in NEU algorithm for two-layer eNMPC

How to Account for Discrete Decisions?

- Slow economic nonlinear model-predictive control (NMPC) **for generation of sequence of operational modes and transition optimization**
  - Low sampling rate
  - **Hybrid (switching) controller**
  - Efficient, robust OC algorithm
- Fast economic NMPC
  - High sampling rate
  - Initial value embedding / suboptimal / neigboring extremal update (NEU algorithm)
- Distributed fast MPC for large-scale systems



Scenario-based Decision Making – Situated Action

Adjust operational strategy to context !

Scenario (market, suppliers, demand, state of plant ...)

Strategy 1

Strategy 2

...

Different objectives

Min cost

Max flexibility

...

Strategy 2

Strategy 1

Strat. ...

Strat. ...

t_0 t_f

Optimal changeover & automatic sequencing

Strategy 1	Strat. 3	Strategy 2

t_0 t_f

Disjunctive Programming Formulation
Multistage Optimization Problem

- Objective: $$\min_{z_k, u_k, p, Y} \quad \Phi := \sum_{k=1}^{n_s} \Phi_k\left(z_k(t_k), p, t_k\right) + \sum_{i=1}^{n_Y} b_i$$
- Dynamic model: $$s.t. \quad f_k\left(\dot{z}_k, z_k, u_k, p, t\right) = 0, t \in [t_{k-1}, t_k], k \in K,$$
- Constraints: $$g_k\left(z_k, u_k, p, t\right) \leq 0, t \in [t_{k-1}, t_k], k \in K,$$
- Initial conditions: $$l\left(\dot{z}_0, z_0, p\right) = 0,$$
- Stage transition conditions: $$z_{k+1}^d(t_k) - m_k\left(z_k(t_k), p\right) = 0, k \in K_m,$$

- Disjunctions: $$\begin{bmatrix} Y_i \\ q_{k,i}\left(\dot{z}_k, z_k, u_k, p, t\right) = 0, \\ r_{k,i}\left(z_k, u_k, p, t\right) \leq 0, \\ s_i\left(\dot{z}_0, z_0, p\right) = 0, \\ z_{k+1}^d(t_k) - v_k^i\left(z_k(t_k), p\right) = 0, \\ b_i = \gamma_i, \end{bmatrix} \vee \begin{bmatrix} \neg Y_i \\ B_{k,i}[u_k^T, p^T, \\ \quad z_k(t_{k-1})]^T = 0, \\ b_i = 0, \end{bmatrix}$$
- Propositional logic: $$\Omega(Y) = True.$$

Vassiliadis et al., 1994, Raman & Grossmann, 1994, Oldenburg et al., 2003, Busch et al. 2005, 2007, Elixmann et al., 2010, Wolf et al. 2014

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Take Home Messages

- The German “Energiewende”
  - ❖ is an ambitious undertaken which is deemed to success;
  - ❖ its success will not only depend on science, though science will be one of the major enablers.
- Research on new materials, components and devices is going strong (@FZJ on PV, RSOFC, batteries …)
- Systems & control needs much more attention and offers great research opportunities:
  - ❖ integrated design (e.g., P2X2P, demand-side management),
  - ❖ integration of planning, scheduling & control,
  - ❖ hierarchical and distributed architectures embedding economic model-predictive control and moving horizon estimation,
  - ❖ (big) data analytics & machine learning, and
  - ❖ many more …

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FINDING TOMORROW TODAY

Mitglied der Helmholtz-Gemeinschaft

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