Aquifer Thermal Energy Storage (ATES) Smart Grids

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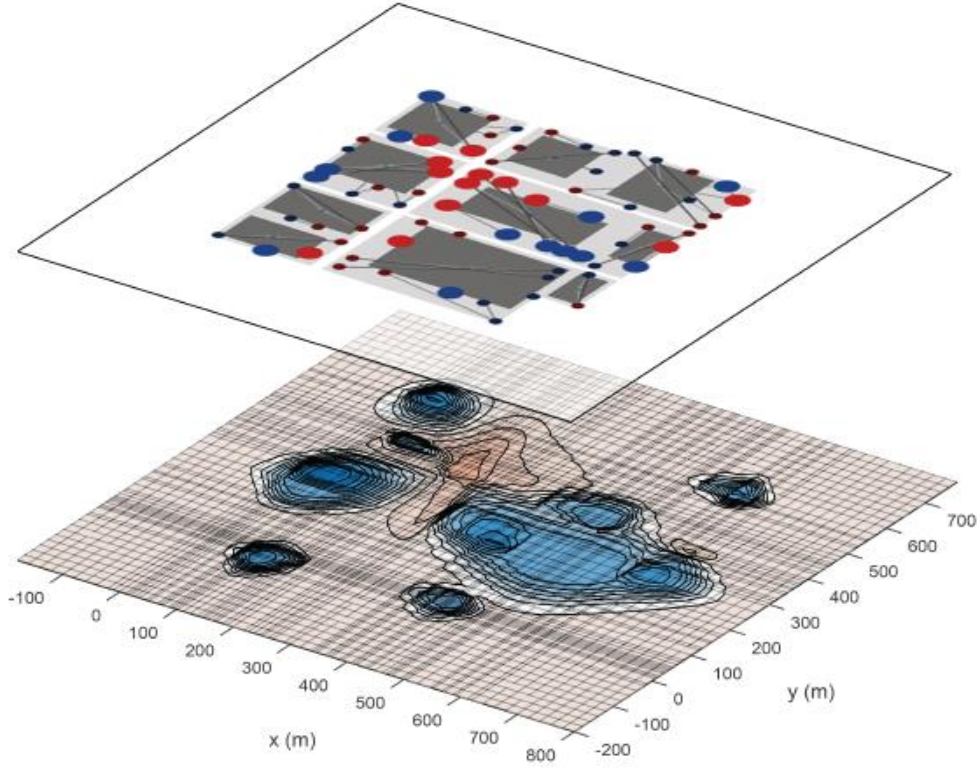

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Netherlands Organisation for Scientific Research

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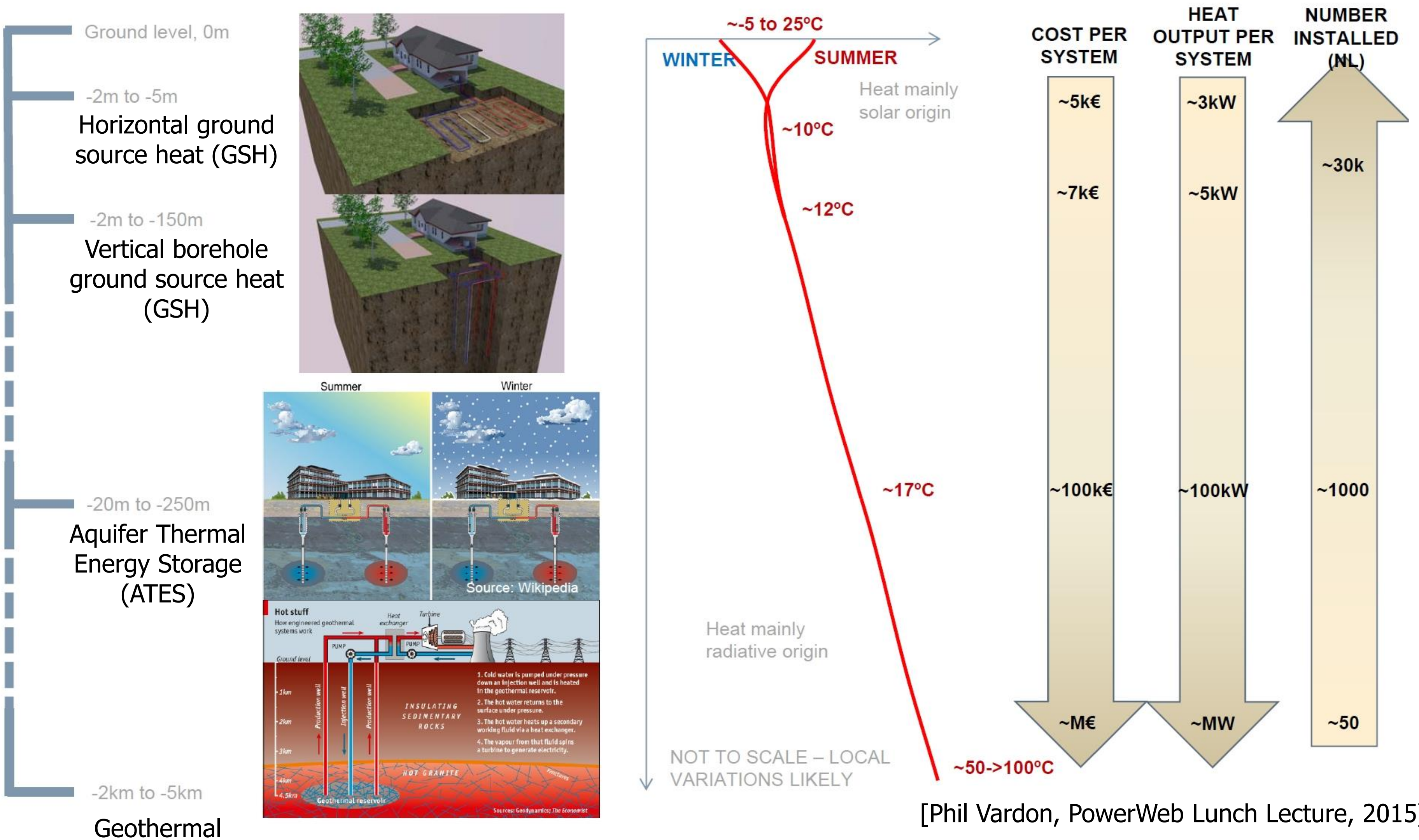
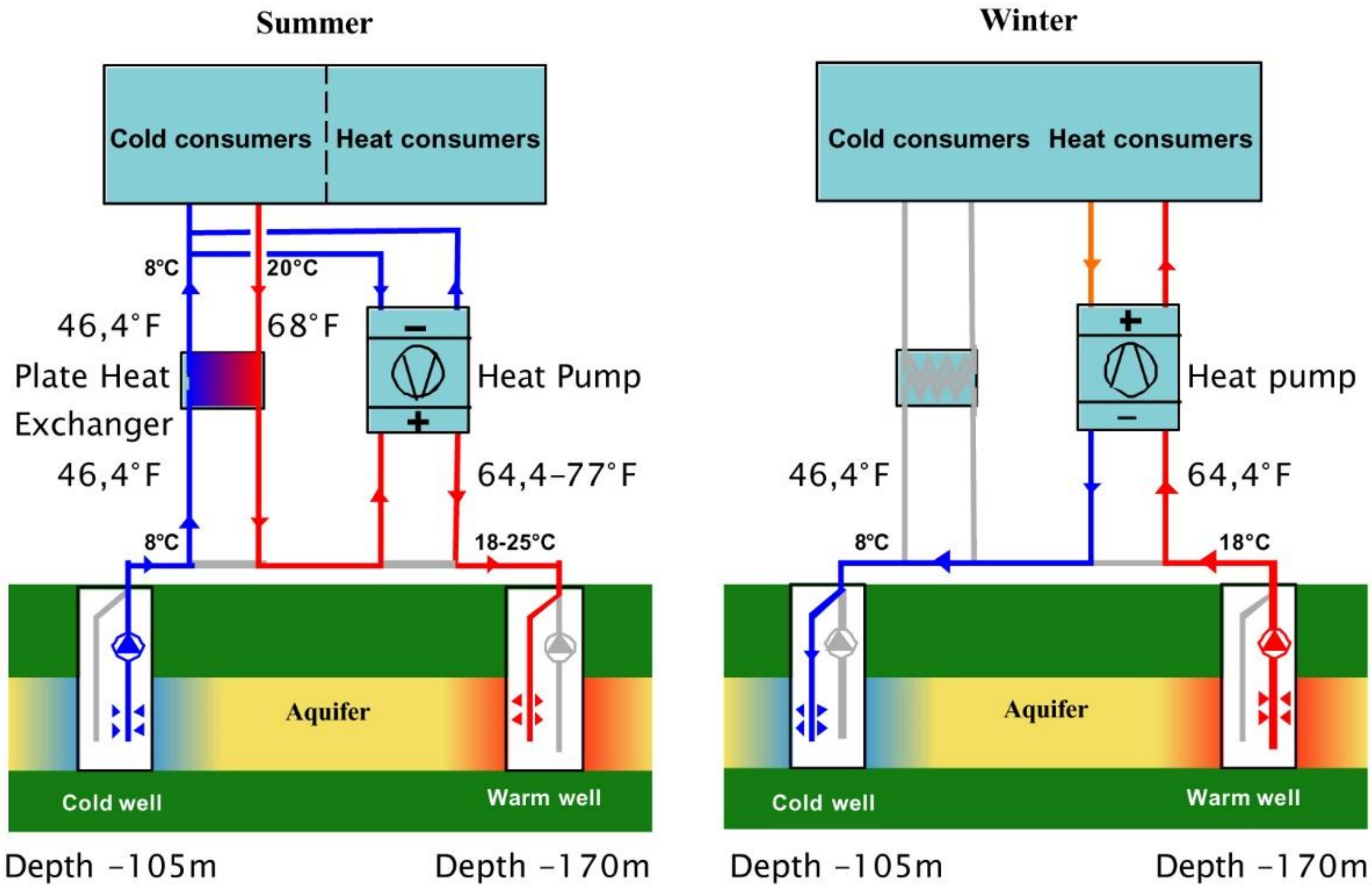
Ground Source Heat Landscape



[Phil Vardon, PowerWeb Lunch Lecture, 2015]

- One-third of energy is consumed within the built environment in NL

Principle of ATES

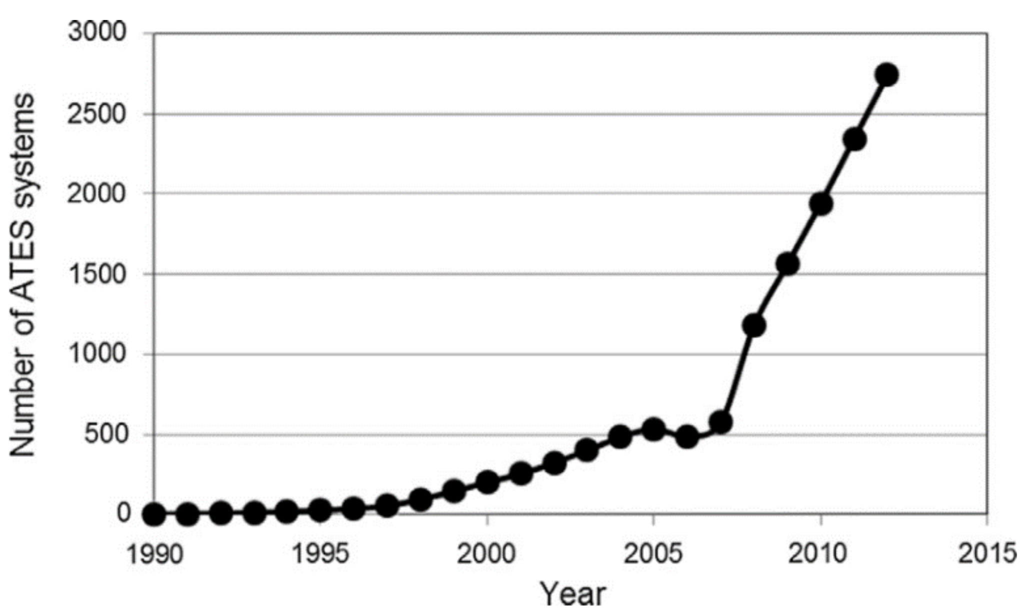


[http://www.amrathamsterdam.com]

- ATES systems act as seasonal energy storage buffers

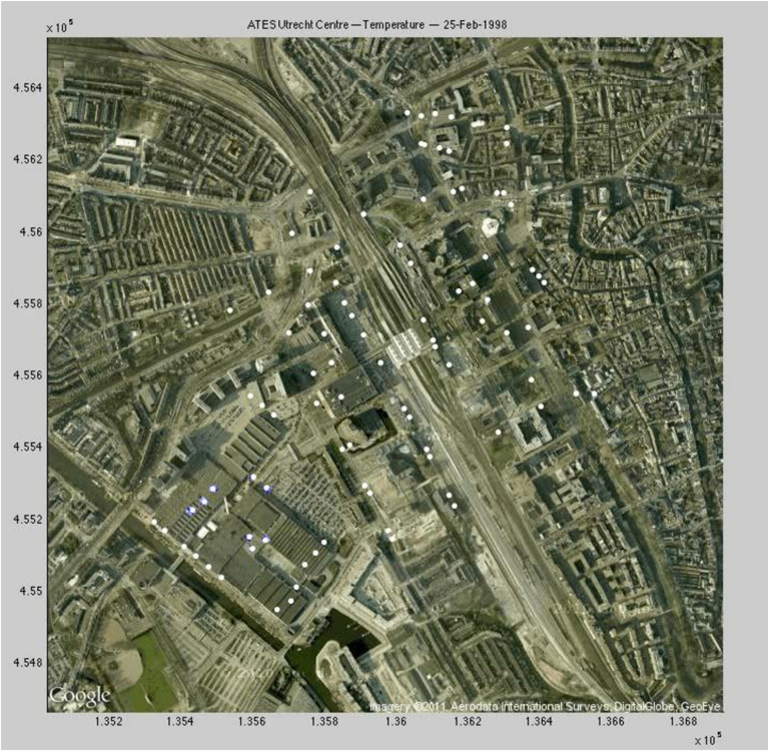
Benefits of ATES

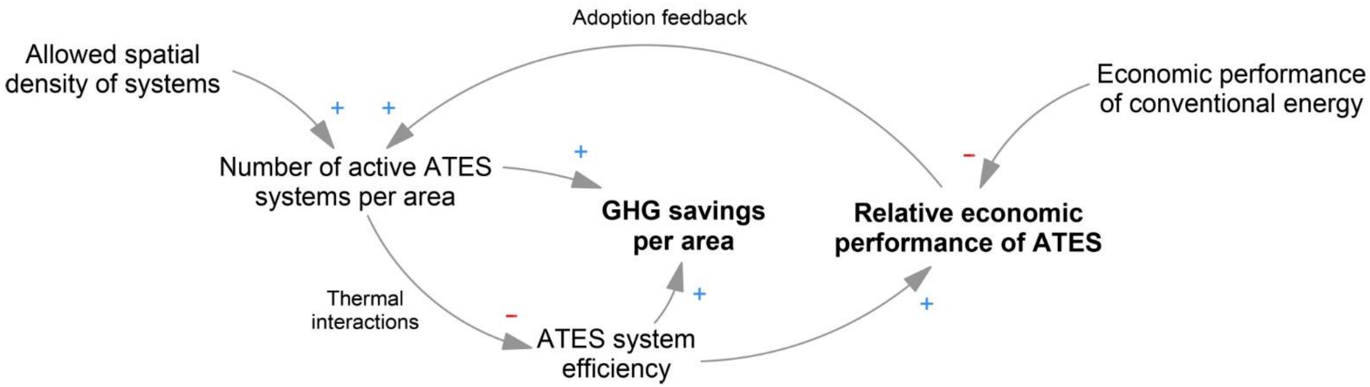
- ATES provides sustainable heating and cooling
- Stores large amounts of low quality thermal energy (typical capacities: few 100 kW per well)
- Can reduce energy use (and GHG emissions) by 50% for large buildings
  - 60-80% energy saving for cooling (80-90% electrical peak reduction)
  - 20-30% energy saving for heating
- Around 3000 systems are in use in NL, rapid growth over the past 10 years



Main Challenges

- How to manage this technology at a larger scale?
- We need more ATES systems to meet GHG emission reduction goals
- ATES systems accumulate in urban areas
- Current policies are too strict for optimal use of subsurface (artificial scarcity)
  - Static permits to avoid thermal interference
  - Unclear trade-off between individual and overall energy savings
  - Coordination is required to prevent negative interaction
- Socio-technical system with complex adoption dynamics:





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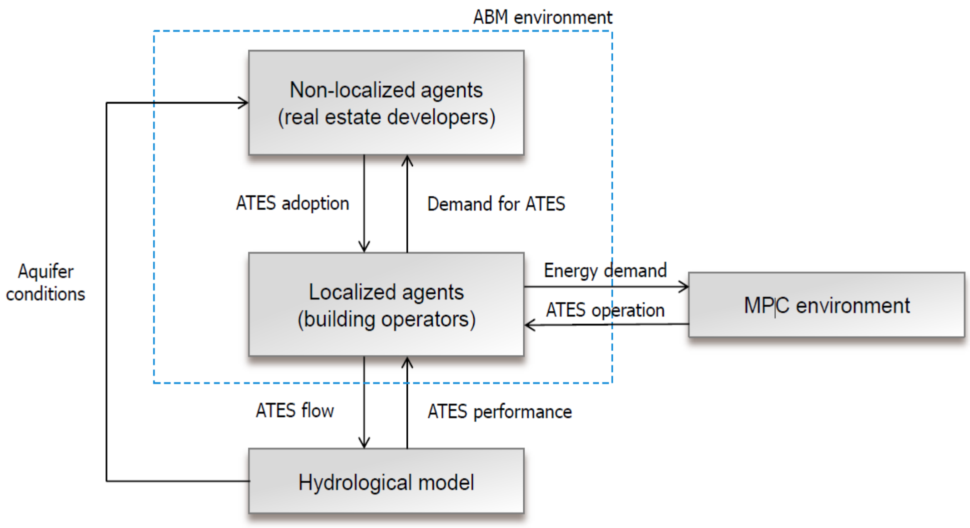
Research Hypothesis and Approach

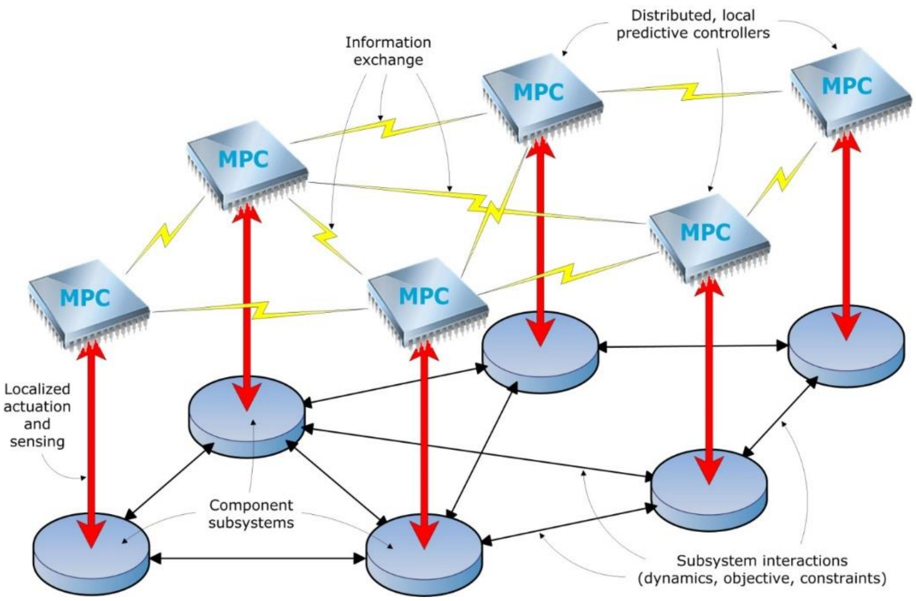
ATES systems can self-organize subsurface space use to increase efficiency

- Facilitate communication and negotiation
- Use distributed stochastic cooperative control to take account of uncertainties and variations in (future) energy demand
- Agent based modeling of socio-technical interactions
- Modeling of subsurface conditions

Agent-based hybrid socio-technical modeling



Distributed model-based predictive control



Multidisciplinary Problem

ATES Integration,
Geohydrology

Martin Bloemendal
(Postdoc – TUD CEG)

Research
team

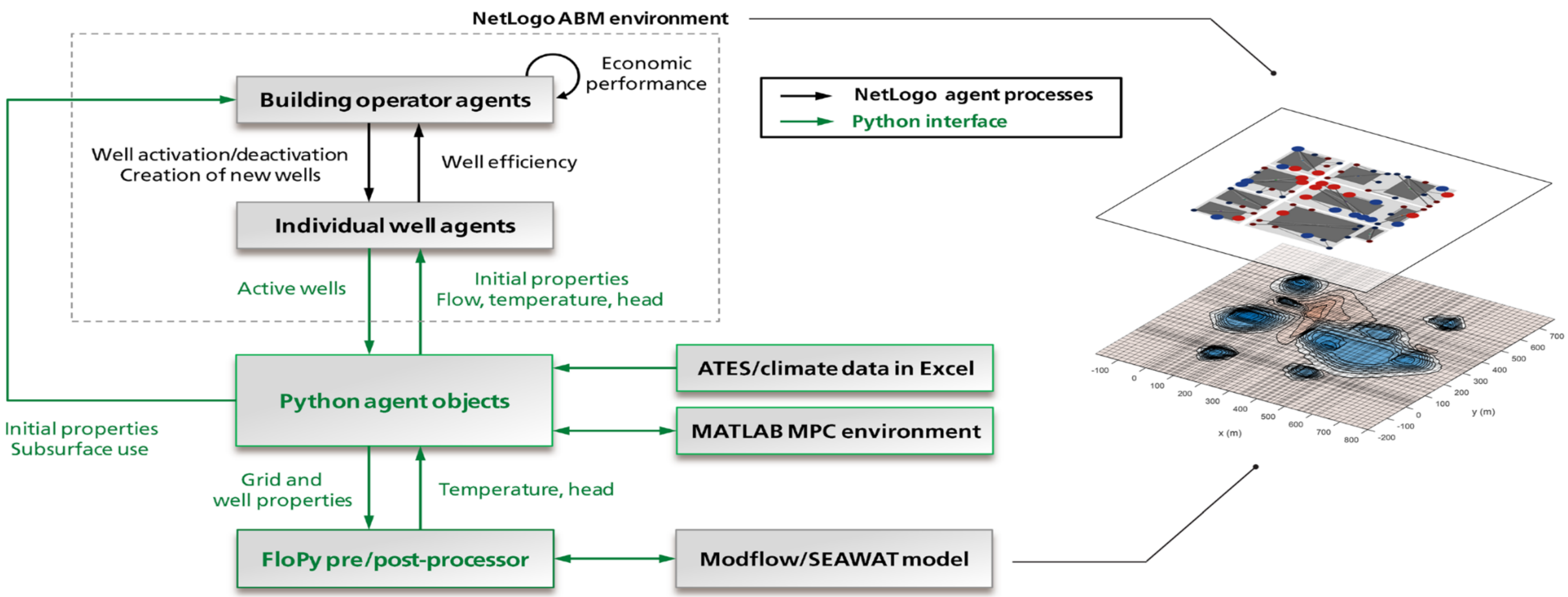
Hybrid Socio-Technical
Modeling

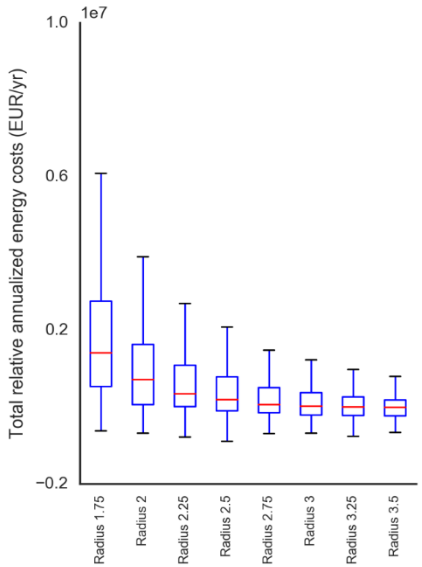
Marc Jaxa-Rozen
(PhD – TUD TPM)

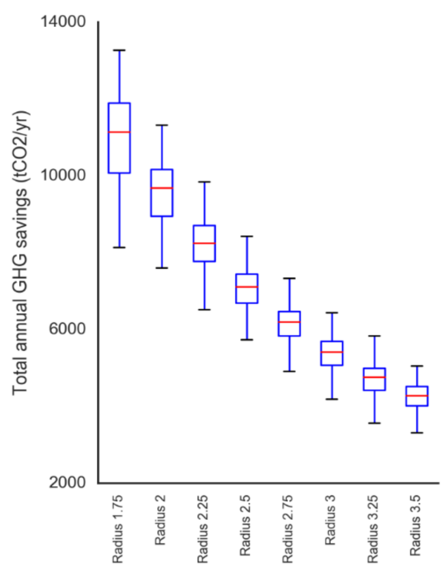
Distributed Stochastic
Cooperative Control

Vahab Rostampour
(PhD – TUD DCSC)

Hybrid Socio-Technical Modeling







- Clear trade-off between individual costs and GHG savings as function of well distance
- Remains present even under uncertainty

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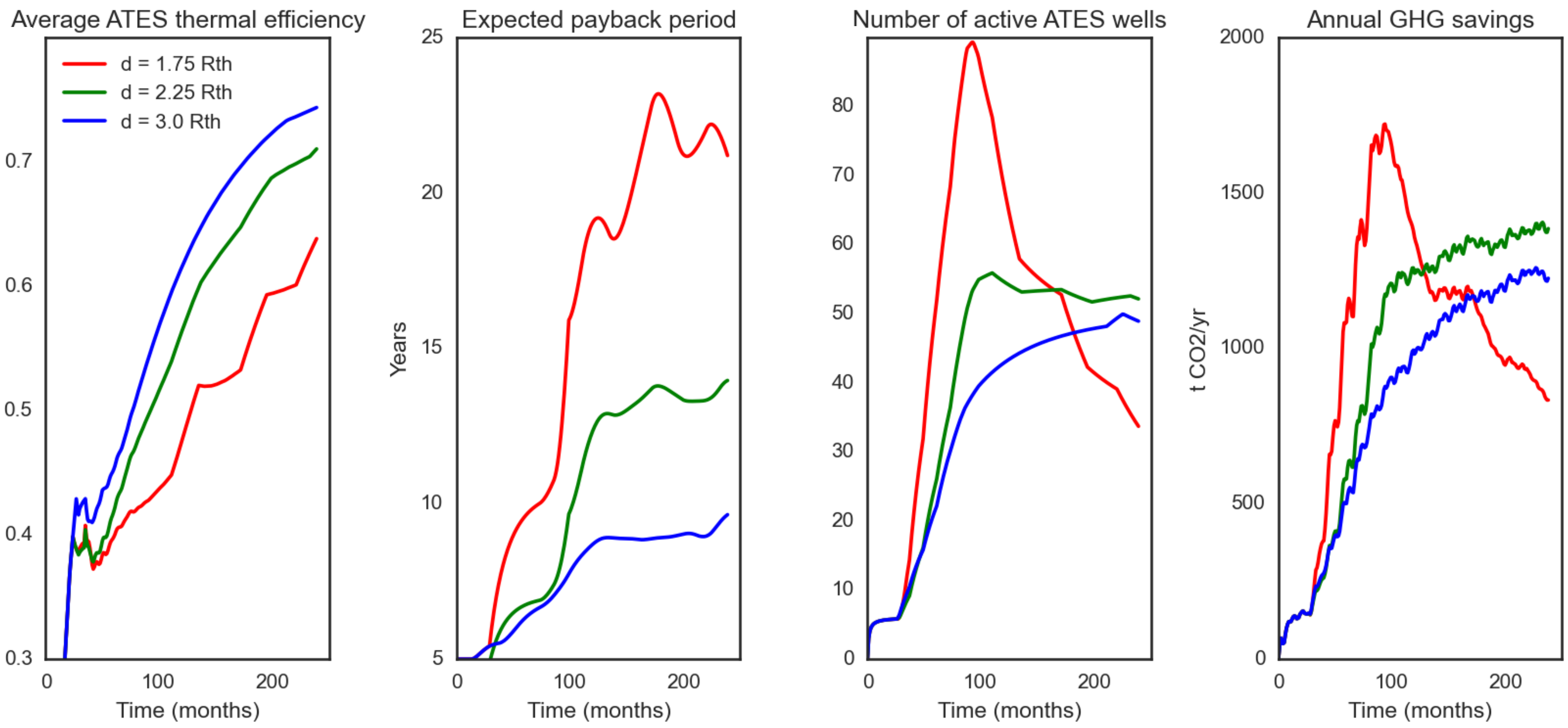
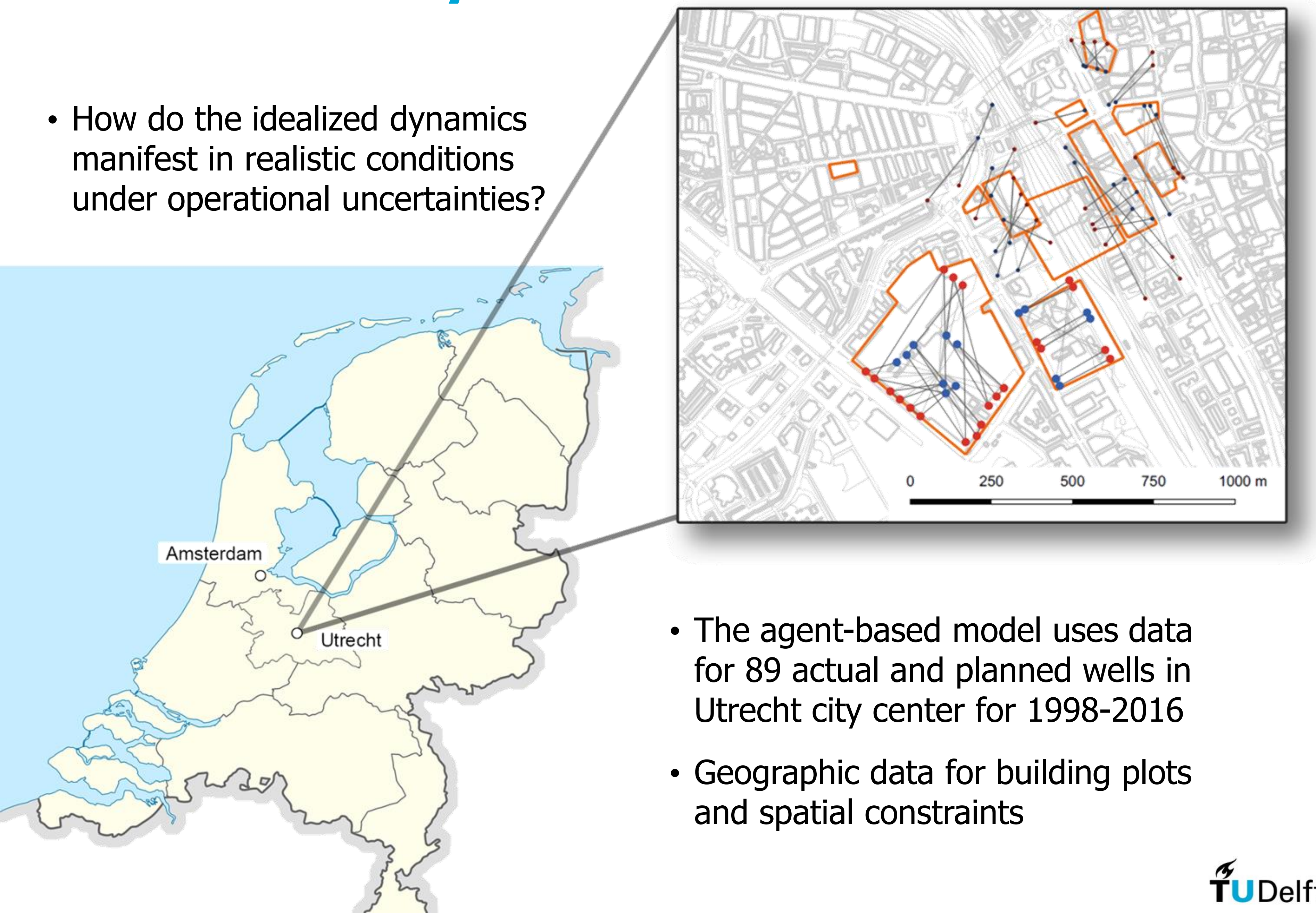
Impact of ATES well density on system dynamics

- Improper spatial planning could lead to a “tragedy of the commons”
- Results on a “sandbox” model with idealized dynamics:



Local Case Study

- How do the idealized dynamics manifest in realistic conditions under operational uncertainties?



- The agent-based model uses data for 89 actual and planned wells in Utrecht city center for 1998-2016
- Geographic data for building plots and spatial constraints

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Preliminary Conclusions

- Lack of feedback between static permits and system operation leads to inefficient outcomes:
  - less than half of permit capacity used
  - significant seasonal imbalances that degrade efficiency due to unforeseen interactions
- Real clearances are likely larger than planned
  - leads to a waste of space for new wells
- Operational uncertainties have at least as much of an impact as planning

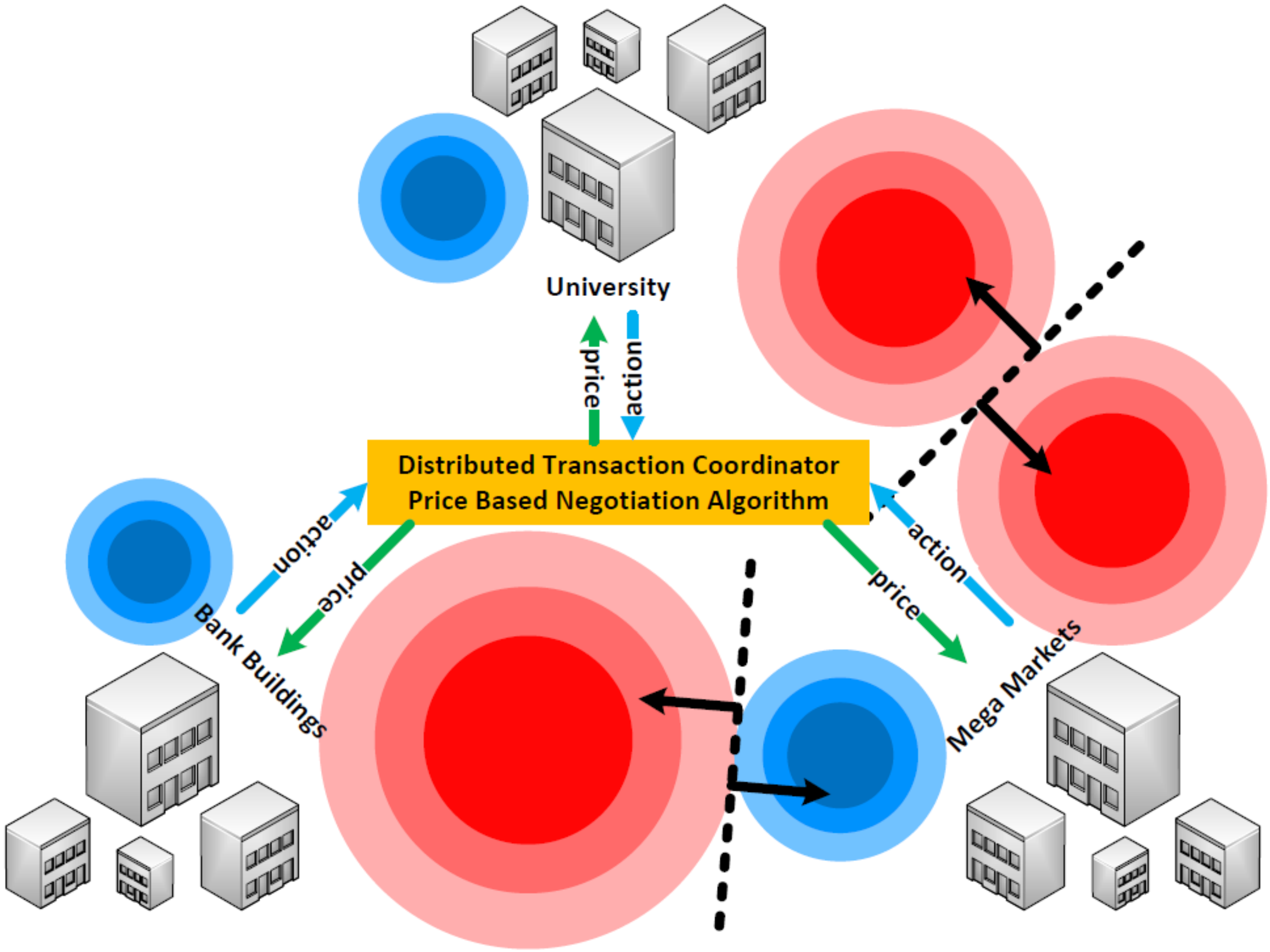
Preliminary Conclusions

- Survey of current ATES users about perceived barriers for technology adoption
- Main hurdles identified as
  - uncertainty about reliability of technology
  - uncertainty about payback
  - limited investment budget
  - current equipment sufficient
  - unclear or complex regulations
- Compared to conventional energy
  - environmental performance is considered much better
  - operational and capital costs, reliability, and operational complexity are considered slightly worse

Paradigm Shift to Reduce Uncertainty?

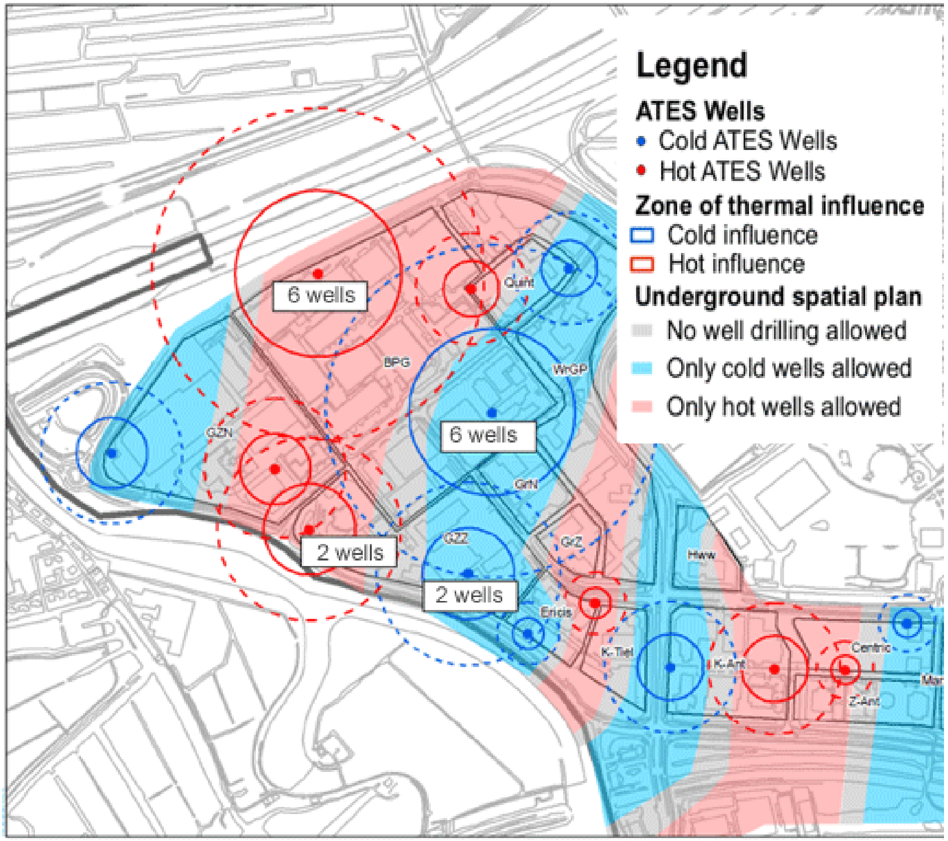
- The most efficient way to reduce uncertainty is to communicate / cooperate between neighboring systems
- How can we develop a self-organizing system that adapts to the operational experience?
- Investigate cooperative control schemes that allow a distributed solution of the underlying stochastic control problem

Cooperative Control Perspective



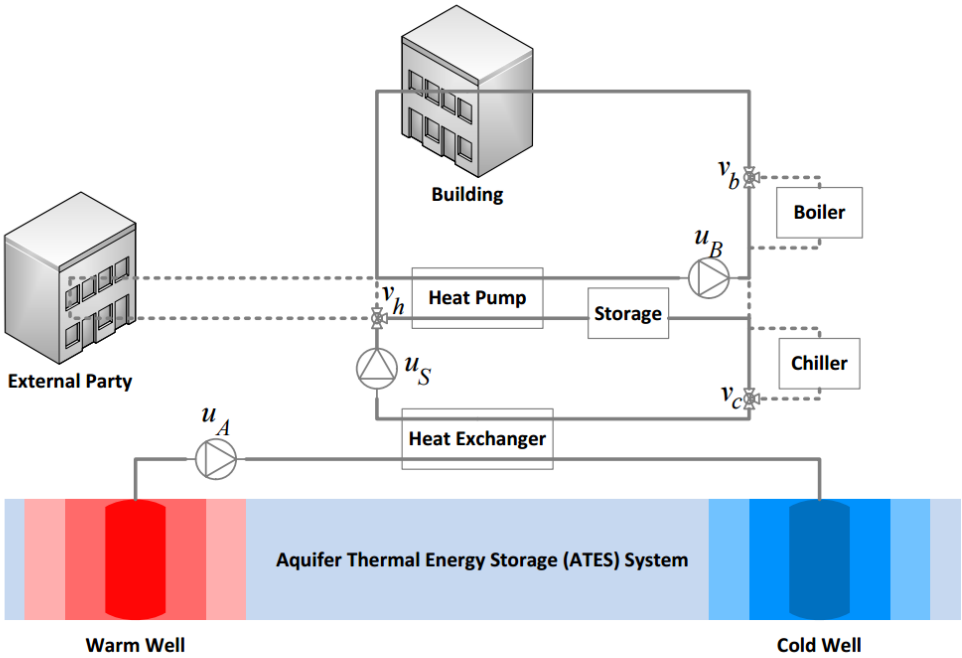
Network of Buildings Using Interconnected ATES

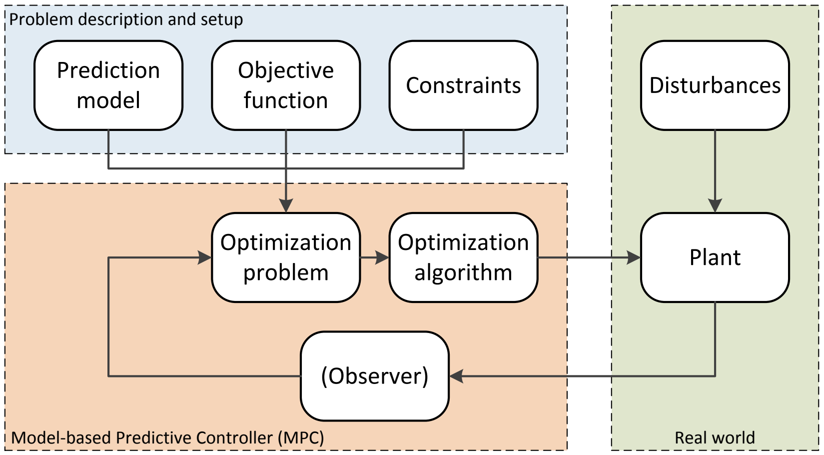
- Spatially distributed system, complex multivariable, switching, nonlinear behavior when coupled with building climate controllers
- Strong exogenous disturbances, stochastic uncertainty
- Modular operation required (plug & play)
- Thermal balance for sustainability (no net energy gain or loss over a whole year while ensuring user comfort)



[Bonte, 2011]

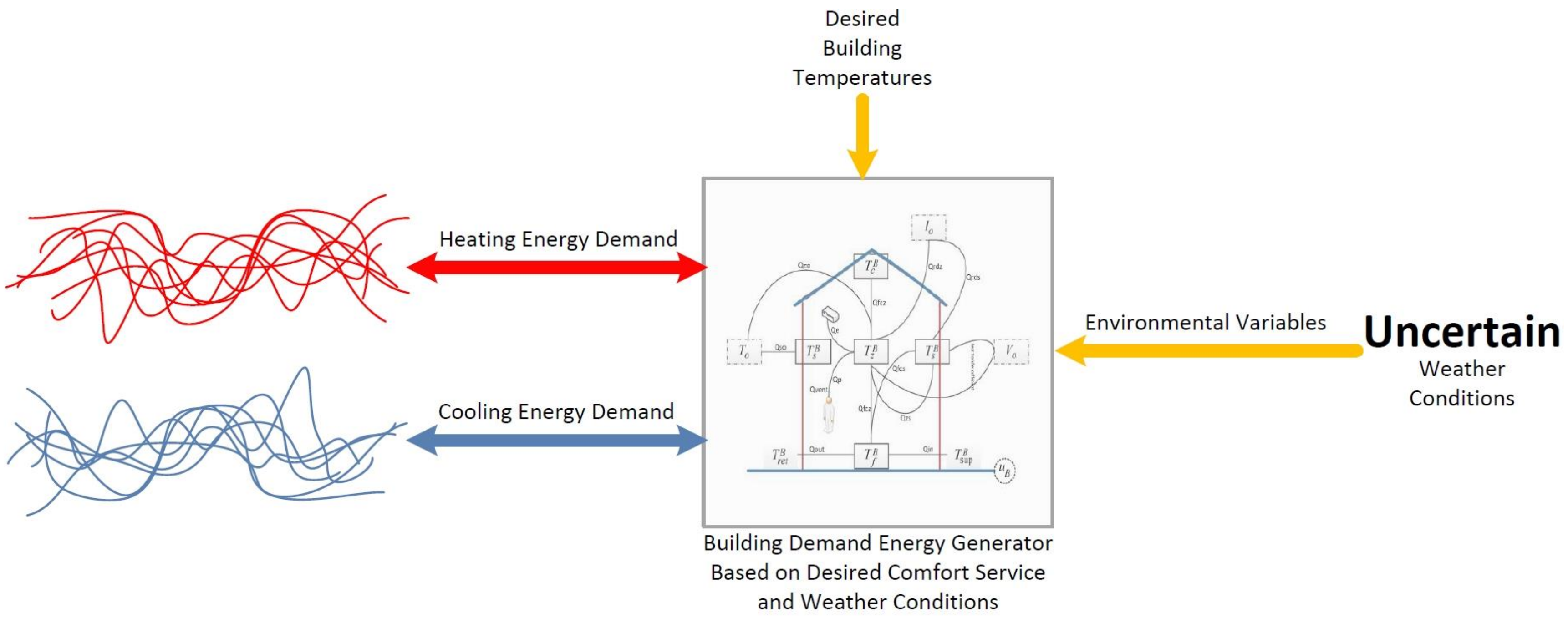
Local Stochastic Control Problem Formulation





- Control-oriented building + ATES model development
- Model predictive control formulation for
  - Tracking desired building energy demand profile for comfort
  - Minimizing building operational cost
  - Minimizing thermal imbalance over long time-scales
  - Switching between modes of operation

Building Energy Demand Generator

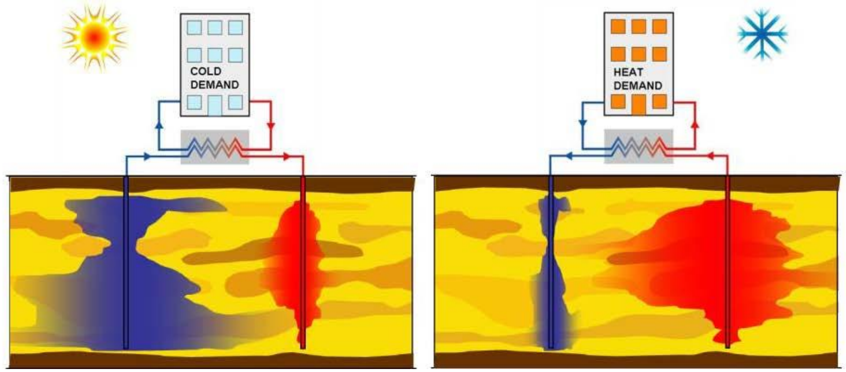


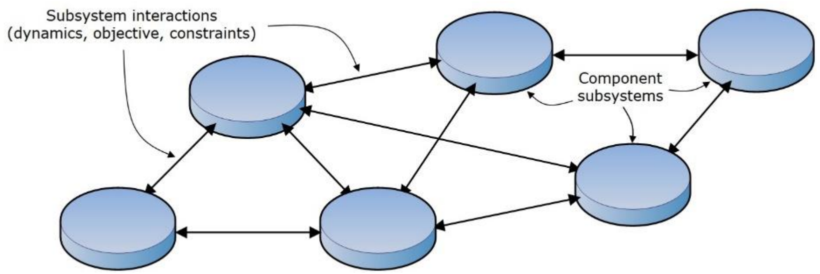
- Complete and detailed building dynamical model
- Desired building temperature (local controller unit)
- Due to uncertain weather conditions, uncertain demand profiles are generated

[cf. Theo Rieswijk, PowerWeb Lunch Lecture, 2016]

Technical Challenges

- Stochastic uncertainty with time-varying constraints (weather, energy demand, aquifer losses etc.)
- Stochastic Distributed MPC based on distributed optimization paradigms
- Modeling paradigm for control versus performance assessment (accuracy vs computation, widely varying temporal and geospatial scales)





Constrained Stochastic Optimal Control Problem

$$\underset{(u_k, y_k)_{k=1}^{M}}{\text{minimize}} \quad J(x_k, u_k) := \mathbb{E}\left[\sum_{k=0}^{M} x_k^\top Q x_k + \sum_{k=0}^{M-1} u_k^\top R u_k\right], \; Q \succeq 0, \; R \succ 0$$

$$\text{subject to} \quad f_k(x_k, u_k, y_k) \leq 0, \; y_k \in \{0, 1\}$$

$$x_k \in \mathcal{X}, \; k = 0, 1, \cdots, M$$

- Control policy parametrization to obtain a less conservative formulation
- Probabilistic interpretation of robustness feature of hard constraints
- Handling mixed-integer optimization together with stochastic programming

Robust Optimization Approach

$$\begin{cases} \min_{x} & c(x) \\ \text{s.t.} & g(x,\delta) \le 0, \quad \forall \delta \in \Delta \\ & x \in \mathcal{X} \end{cases}$$

- Provides a guaranteed level of performance
- Constraints must be satisfied for every disturbance realization in Δ (worst-case)
- Disturbance realizations are treated equally likely (conservative)
- Often intractable problem formulation due to the unknown disturbance set Δ

Chance Constrained Optimization Approach

$$\begin{cases} \min_{x} & c(x) \\ \text{s.t.} & \mathbb{P}\left[g(x,\delta) \leq 0\right] \geq 1-\varepsilon \\ & x \in \mathcal{X} \end{cases}$$

- Relaxed version of robust optimization
- Constraints must be satisfied only for most disturbance realizations except for a set of probability $\leq \varepsilon$
- Need to know the probability distribution
- Nonconvex optimization problem and in general hard to solve

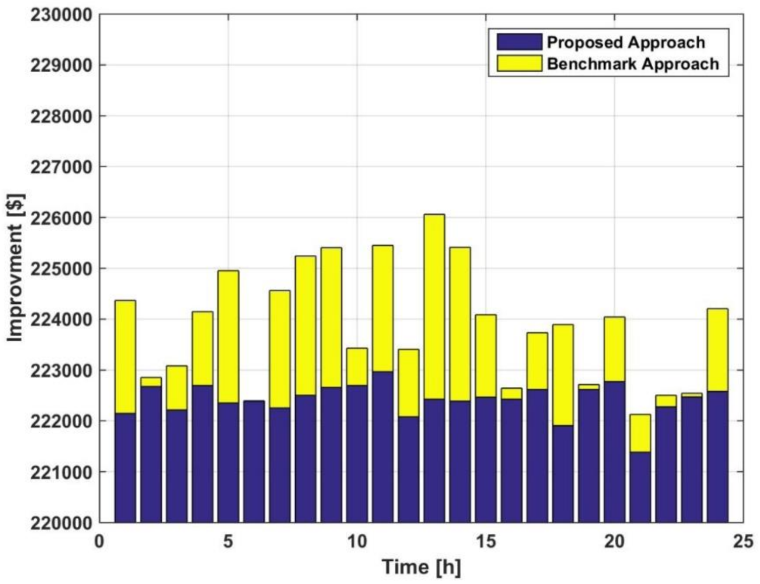
Randomized Approximation (Scenario Approach)

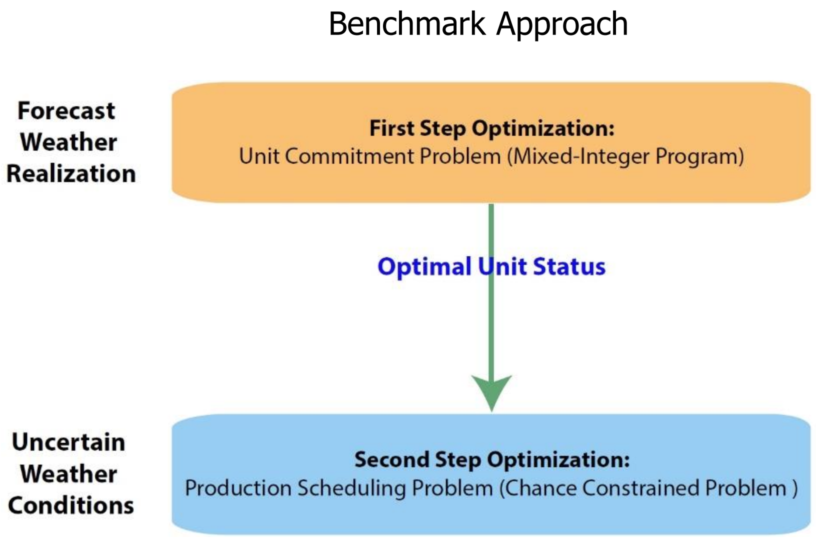
$$\begin{cases} \min\limits_{x} & c(x) \\ \text{s.t.} & g(x, \delta_i) \leq 0, \quad \forall i \in \{1, \cdots, N\} \\ & x \in \mathcal{X} \end{cases}$$

- Computationally tractable approximation to chance constrained programs (but can be conservative)
- Only a finite number of uncertainty realizations (scenarios) are needed
- Relies on historical data of the uncertainty
- Leads to a convex optimization problem

Nonconvex Randomized Approximation

- Provides a tractable formulation to solve mixed-integer stochastic programs
- A priori probabilistic guarantee on the feasibility of the optimal solution

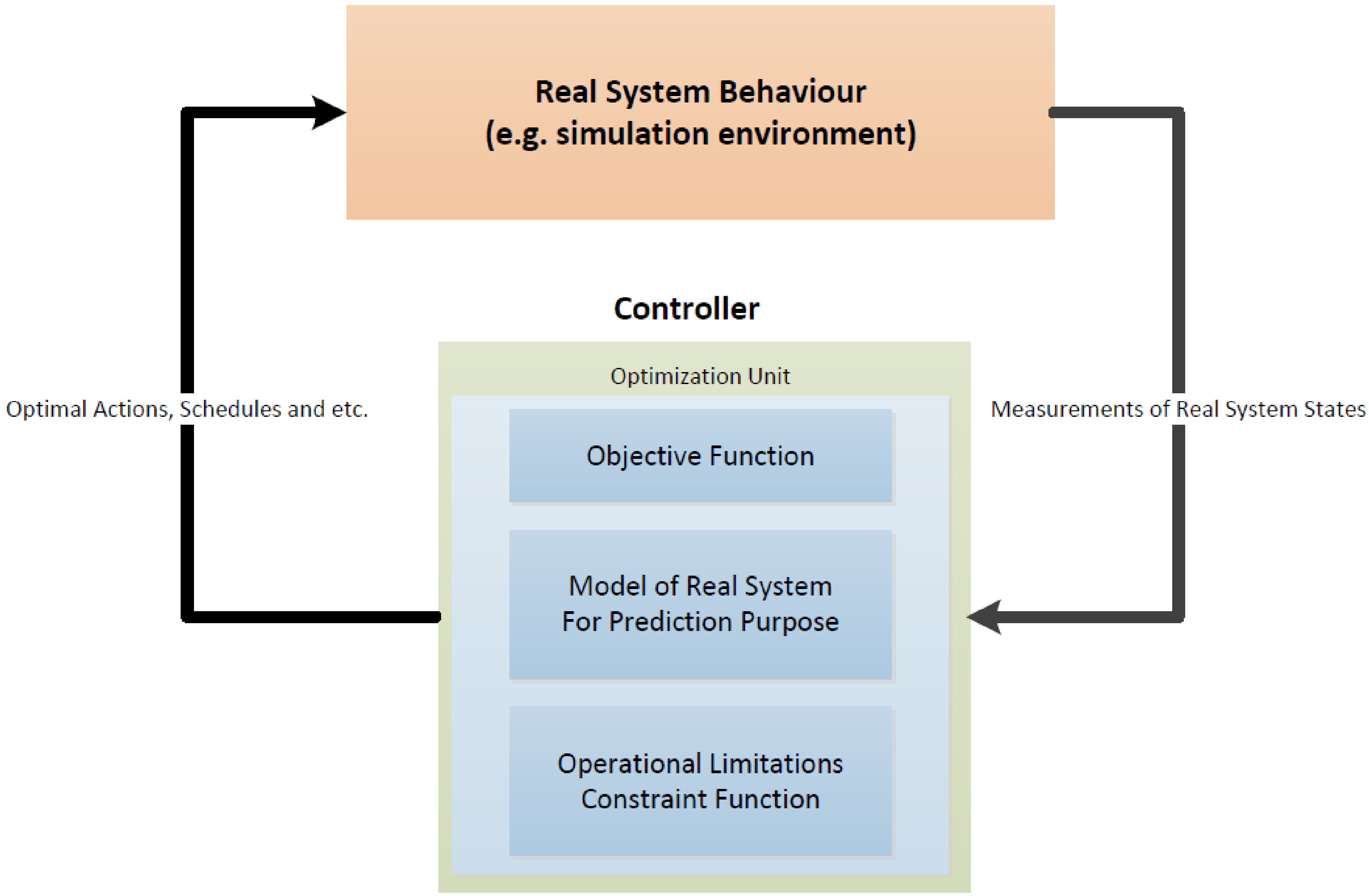




[Rostampour - Keviczky, ECC, 2016]

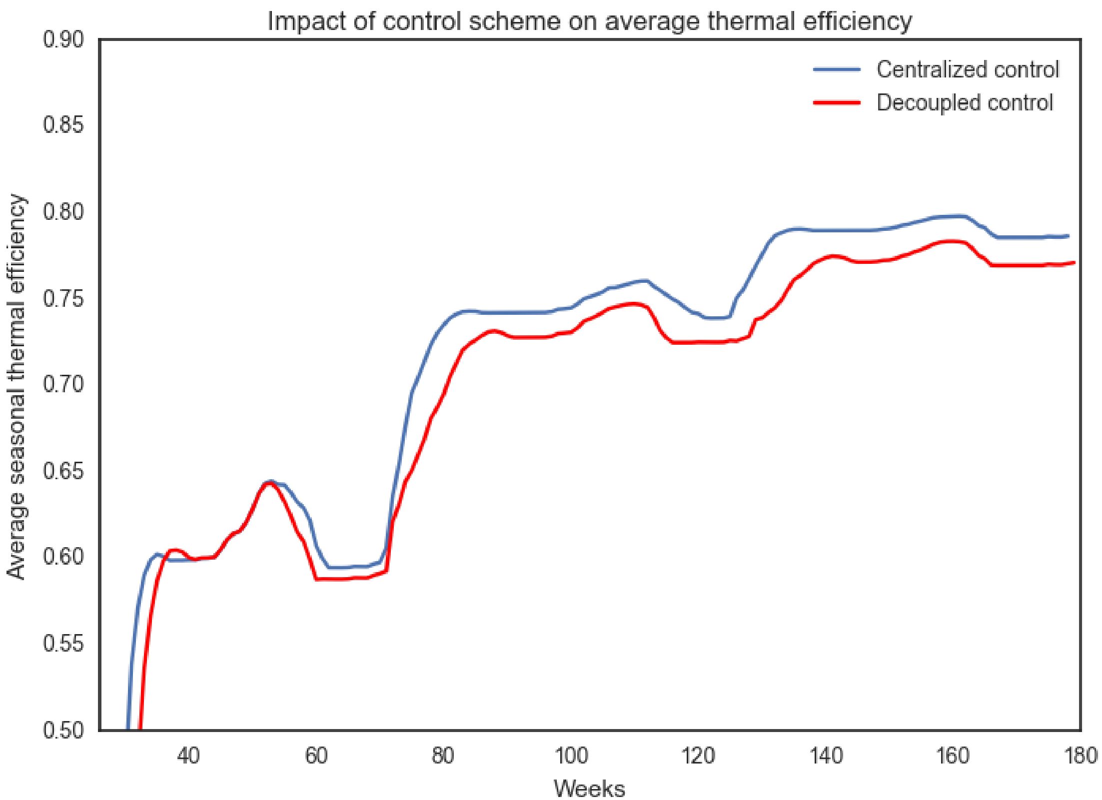
- Currently investigating distributed and hierarchical implementations using ADMM and proximal minimization type algorithms [W.W. Ananduta, MSc thesis, 2016]
- Numerical study shows almost centralized performance, formal convergence results are under development

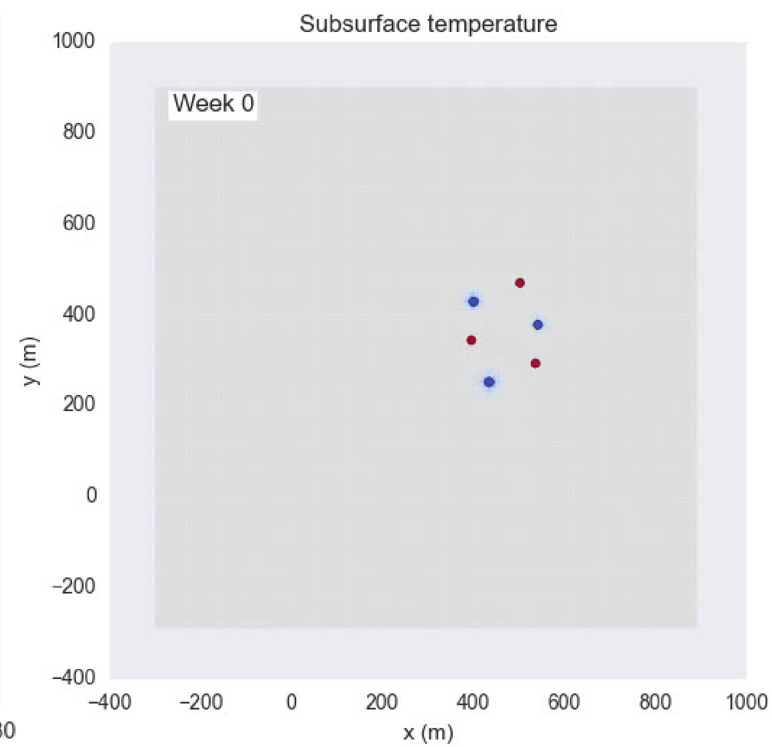
Closed-Loop Interconnection for Simulation



Preliminary Results for Three Agents

- Centralized control with perfect information sharing (aims to prevent overlap between wells of opposite temperatures)
- Decoupled, local controller without any communication or knowledge of neighbors





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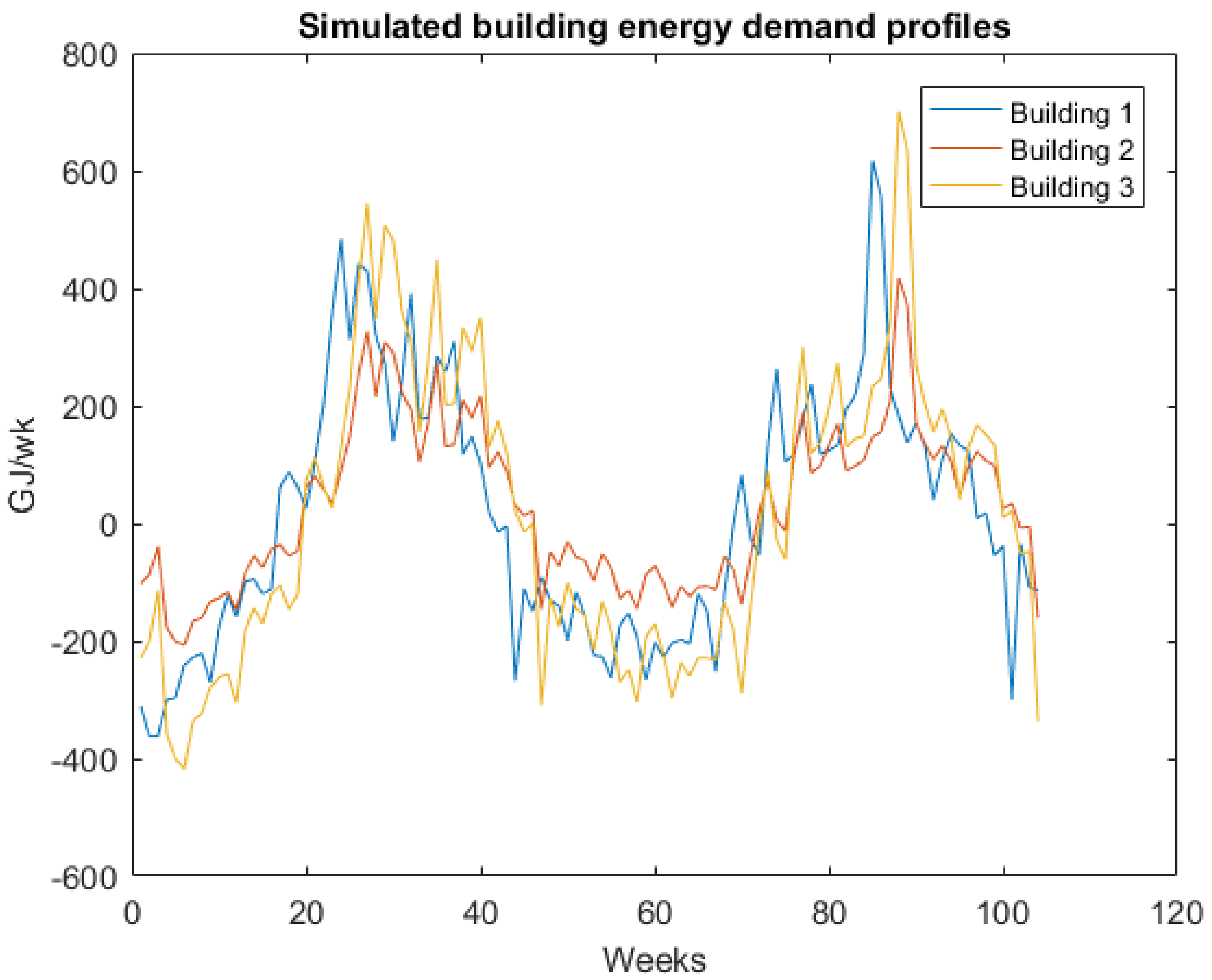
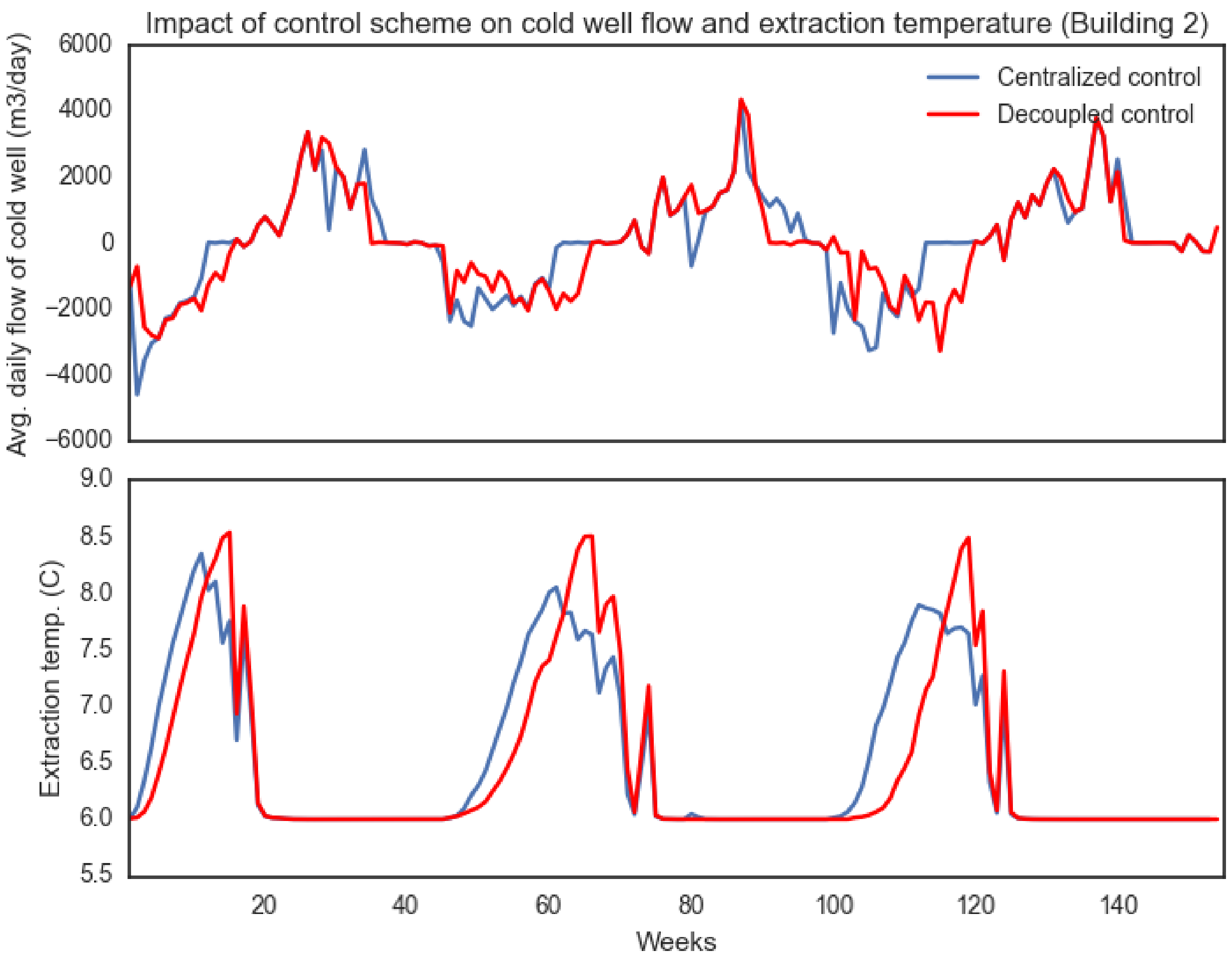
Preliminary Results for Three Agents



Preliminary Results for Three Agents

- The centralized controller enables higher efficiency by better managing the negative thermal interactions between wells of opposite temperatures.



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Next Steps

- Case study for larger-scale, regional ATES development in Amsterdam ($212\ km^2$, 478 wells)
- Self-organization as a way to deal with technical/policy complexity
- Assess the potential benefits of cooperation
  - Level of increased efficiency
  - Sharing of stored thermal energy
- Develop control algorithms for distributed implementation
  - Handle local and shared uncertainties
  - Probabilistic feasibility guarantees of interaction constraints
  - Ensure a certain level of performance
- Online optimization based data-driven approach to decision making under uncertainty
- Investigate cooperative control with privacy-aware information handling
- Results could be used for advising policy changes, mechanism design
- Pilot implementation project in Amsterdam

Partners

PRIVA

KWR
Watercycle Research Institute

Tauw

TU Delft

(3mE, TBM, CiTG)

waternet

DWA

NWO
Netherlands Organisation for Scientific Research

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