Willkommen
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Techniques and tools for distributed energy system modeling & optimization

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sccer | future energy efficient buildings & districts

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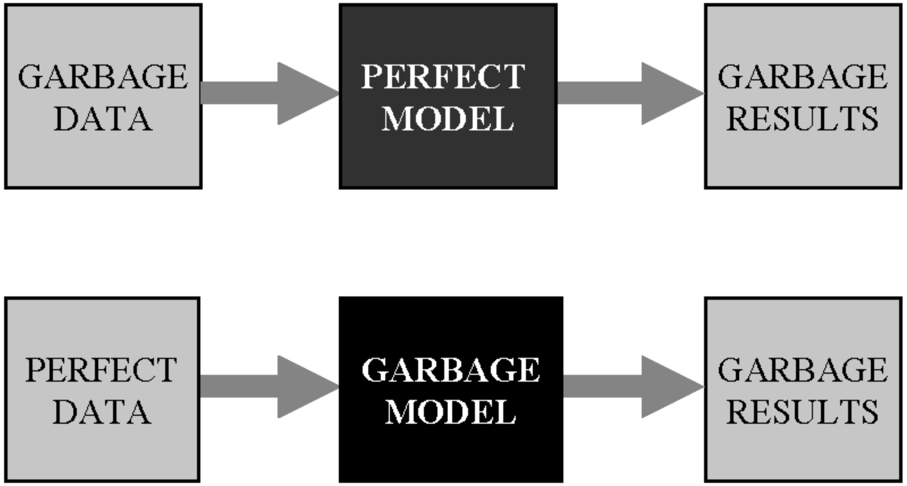
Building on the basic energy hub concept

“garbage in, garbage out”



- To avoid “garbage models”, we need to augment the basic energy hub concept.
- By extending it with:
  - More accurate technical representations
  - Representation of uncertainty
  - Representation of networks
  - …

Extending on the basic energy hub concept

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1. Improving technology representation
2. Representing networks
3. Improving computational efficiency
4. Multi-objective optimization
5. Dealing with uncertainty

Representing networks

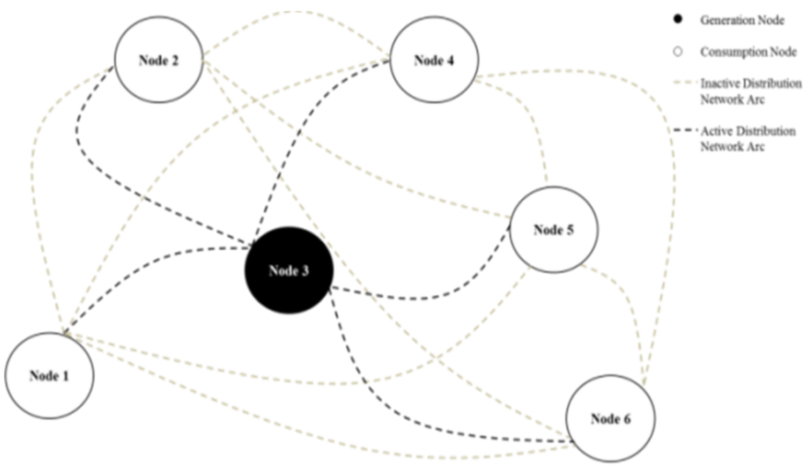
What's the problem?

Basic energy hub formulations aggregate all components/buildings into a single "node", thus neglecting the influence of networks.

- Networks constrain how we can move energy between buildings, and thus can constrain our ability to reach sustainability (or other) targets.

What can we do?

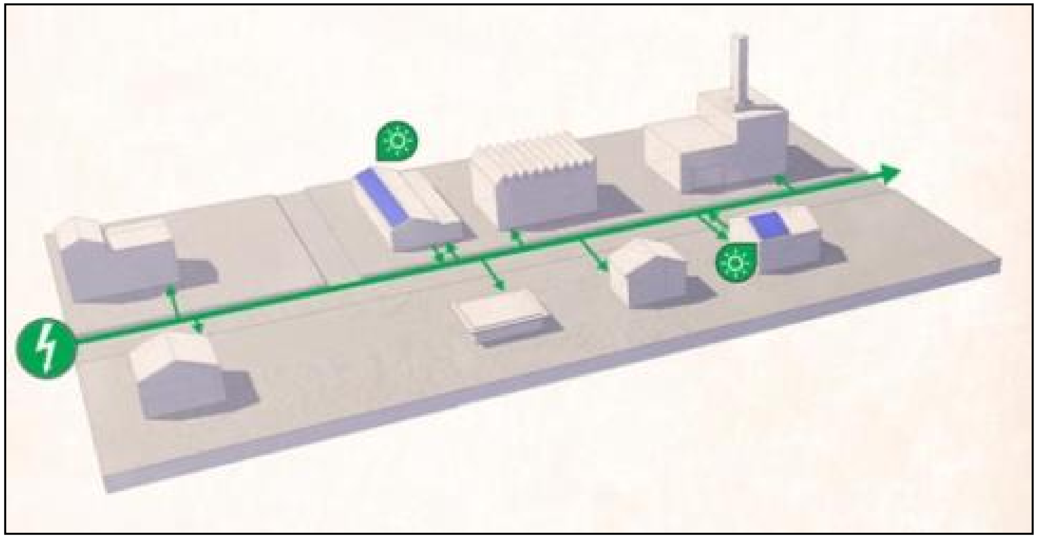
Model the system as being composed of multiple nodes/hubs with network elements connecting them.

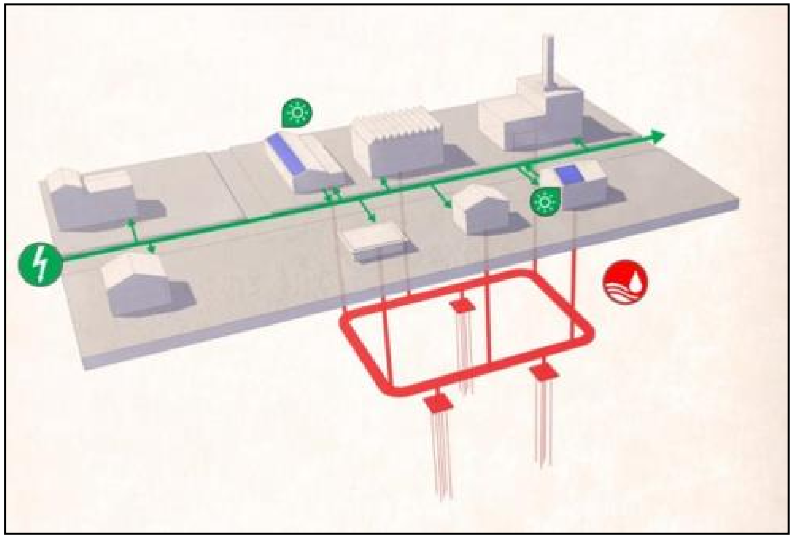


Representing networks – Why is this important?

To improve energy performance…

- Under what conditions should we use only the **electricity grid** to cover electricity and heat demand?
- Under what conditions is a **thermal network** advantageous?
- Thermal networks: How to **connect buildings**? What **temperature levels**?
- Electricity networks: Influence of **grid constraints**?





Representing networks - Equations

Energy flowing out of the node (from node i to j)

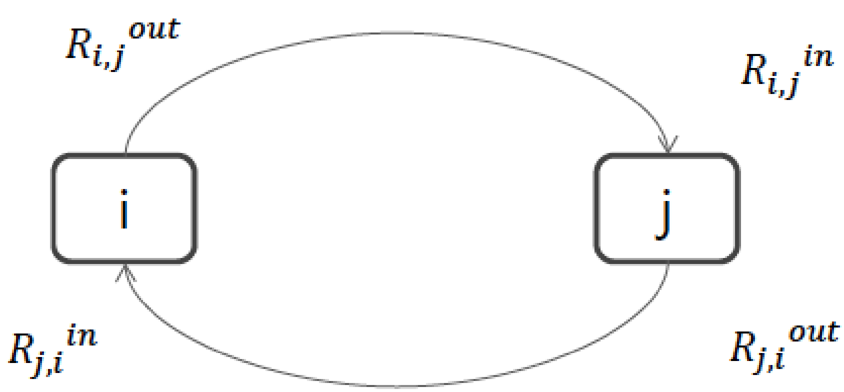
Energy flowing into the node (from node j to i)

Modified load balance constraint:

$$L_k(t) = \underbrace{\Theta_{k,m} \times P_m(t)}_{\text{conversion}} + \underbrace{A_n^{dis} Q_n^{dis}(t) - Q_n^{ch}(t)}_{\text{storage}} \underbrace{+ R_{i,j}{}^{out}(t) - R_{j,i}{}^{in}(t)}_{\text{network}}$$

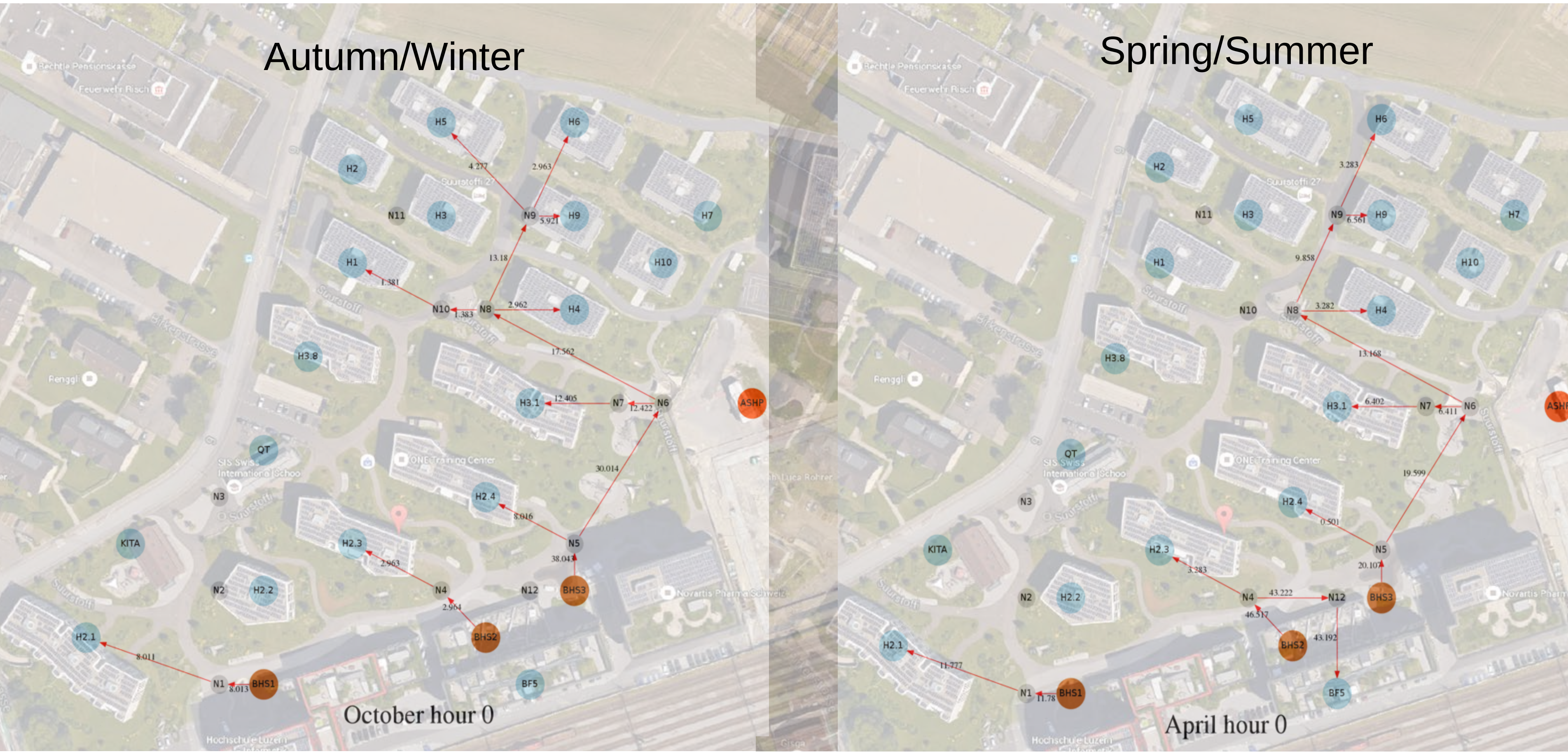
Equation to account for network losses: $R_{i,j}{}^{out}(t) = A_R R_{i,j}{}^{in}(t)$

A_R = network loss



Representing networks – Example Suurstoffi Areal

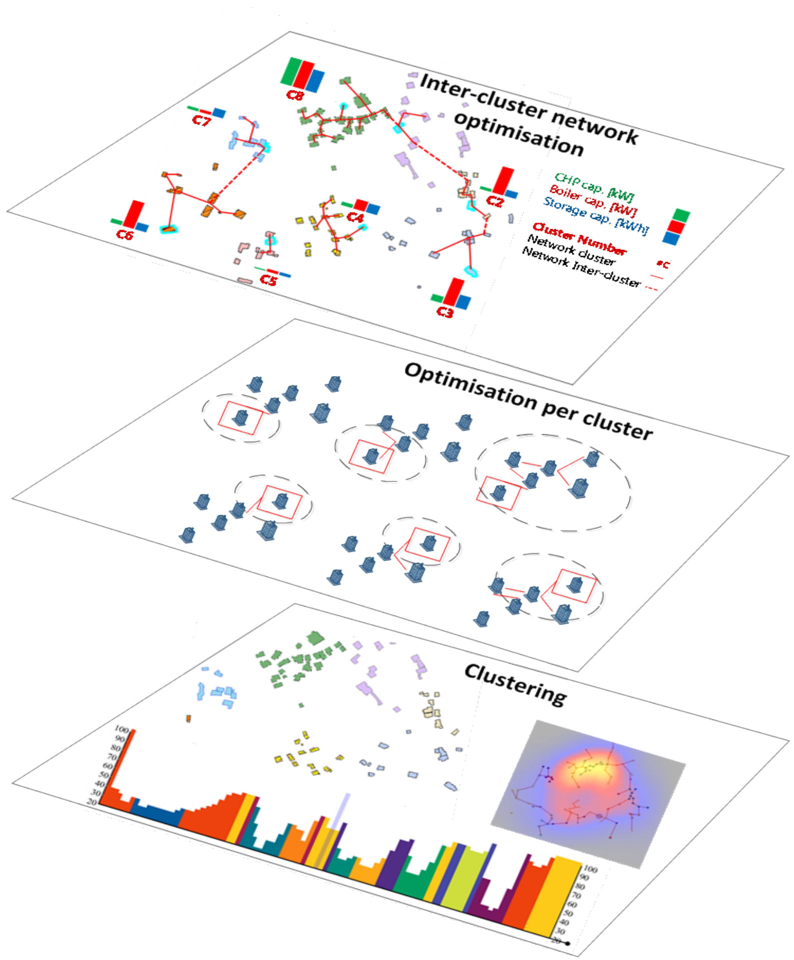
Optimal heat flux (kWh/h) between buildings in a thermal network during different hours of the year, Suurstoffi Areal, Risch-Rotkreuz

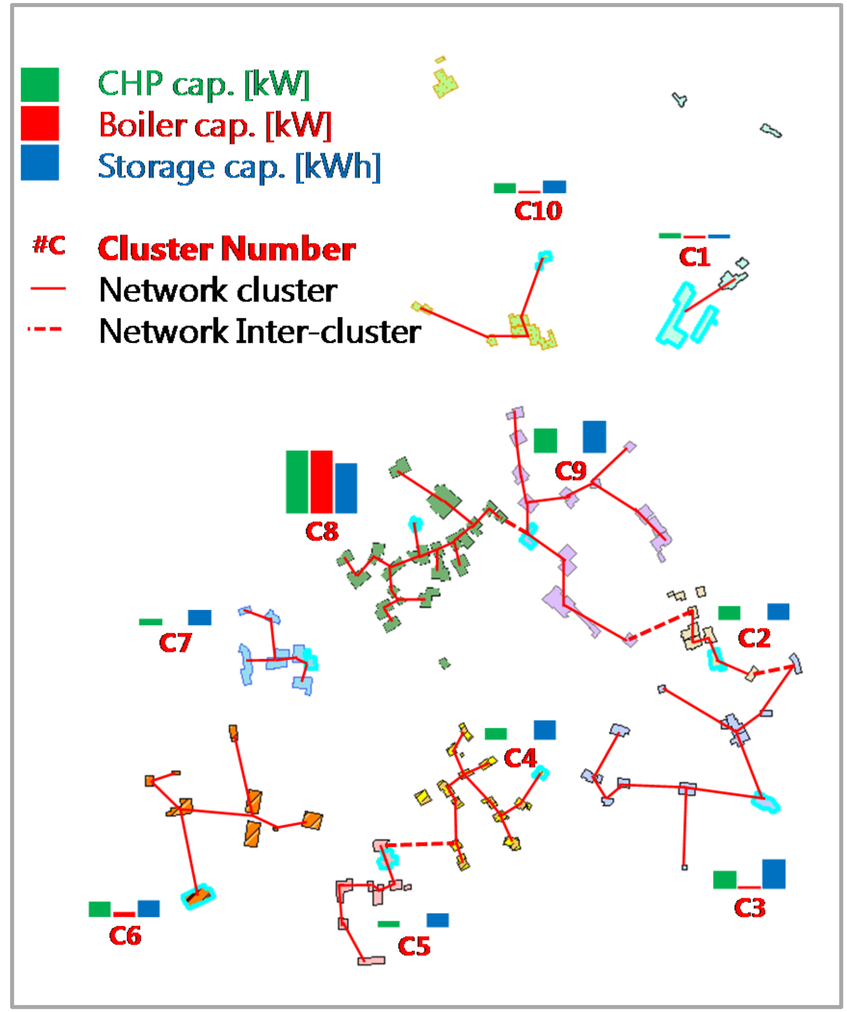


Source: A. Prasanna, Empa-UESL

Representing networks – Optimizing network layout/sizing

Optimizing the clustering of buildings in urban areas into distinct thermal networks





Marquant J., Omu A., Evins R., Carmeliet J. 2015. Application of spatial-temporal clustering to facilitate energy system modelling. Building Simulation 12/2015, Hyderabad, India

Improving computational efficiency

Optimisation Method	Strengths	Limitations
LP (Simplex)	Scalability Global optima	No discrete variables Linearisation Deterministic
MILP (Branch and Cut)	Global optima Discrete variables Scalability (to a degree)	Linearisation Deterministic
MINLP (Direct Search)	Discrete variables Non-linear functions	Local optima Deterministic Scalability
MINLP (Heuristics)	Discrete variables Non-linear functions	Optima not guaranteed Deterministic Scalability
MINLP (Meta-heuristic)	Discrete variables Non-linear functions Probabilistic	Scalability Optima not guaranteed

MILP = mixed-integer linear programming

3. Improving computational efficiency

What's the problem?

- MILP model size scales exponentially with the number of integer variables
- Complex energy hub model formulations – especially with many discrete variables – become very difficult to solve using conventional MILP solvers.

What can we do?

Develop models that:

1. Minimize the number of time intervals and nodes
2. Use alternative optimization approaches

Specifically:

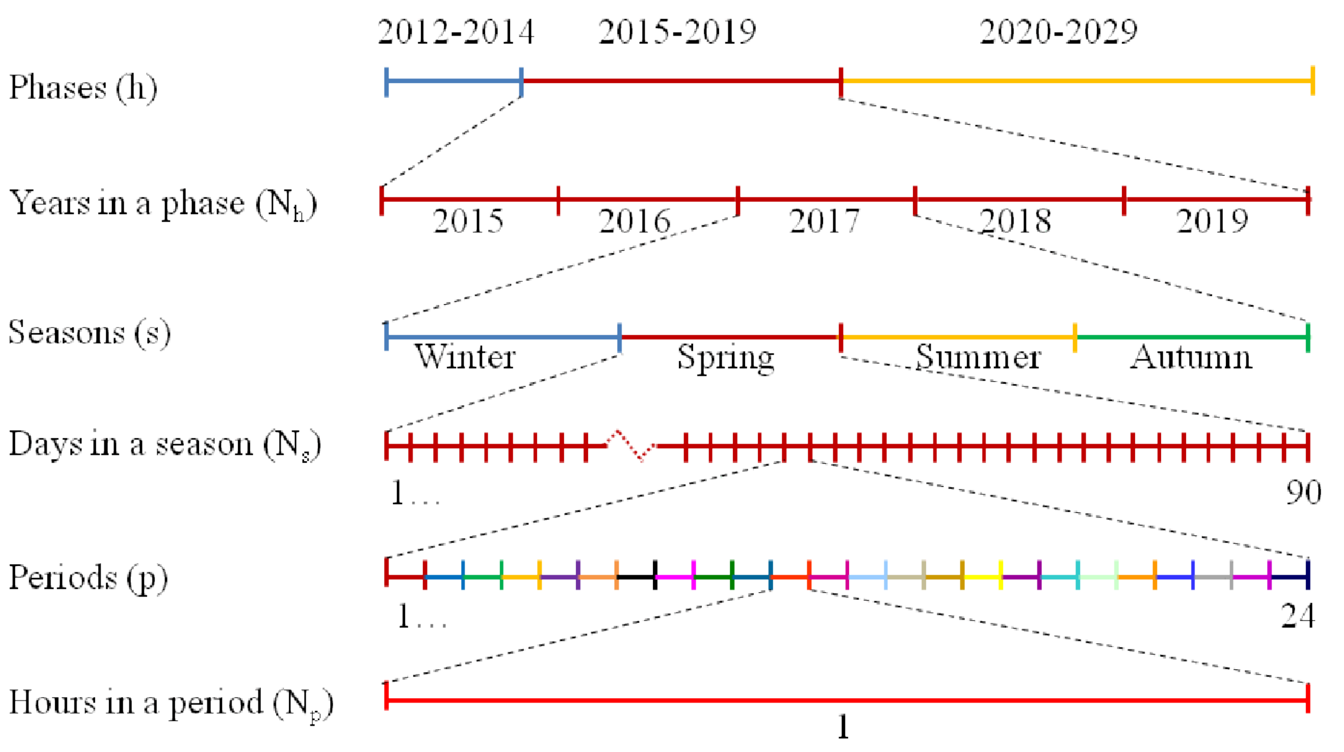
1. Temporal discretization
2. Temporal decomposition
3. Spatial clustering
4. Bi-level & hyper-heuristic optimization

Improving computational efficiency - Temporal discretization

- What time period are we interested in optimizing?
- Into how many discrete time periods to we divide the overall time period?
- Every minute, hour, day, week?
- Every day in the year, or just “representative” days?
- How do we choose days which are sufficiently representative?

The fewer discrete time periods you have, the simpler/quicker your optimization problem will be.

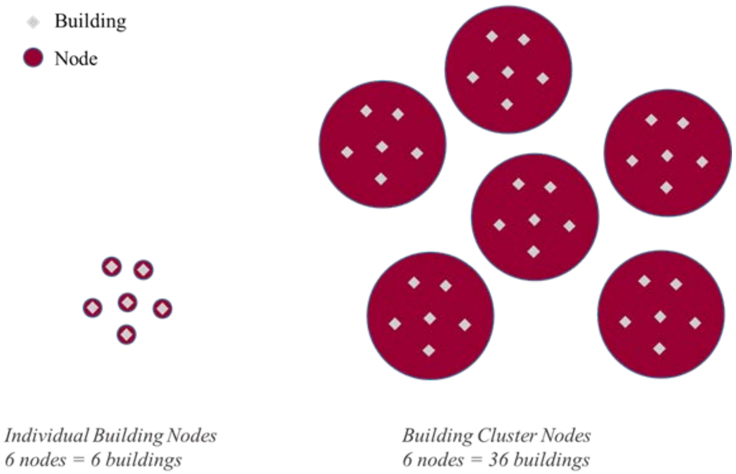
How to reduce the number of discrete time periods **without compromising accuracy**?



J. Marquant, R. Evins and J. Carmeliet (2015). Reducing Computation Time with a Rolling Horizon Approach Applied to a MILP Formulation of Multiple Urban Energy Hub System. Procedia Computer Science, 51: 2137–2146

Improving computational efficiency - Spatial clustering

Instead of representing each building individually, we aggregate buildings into **clusters**.



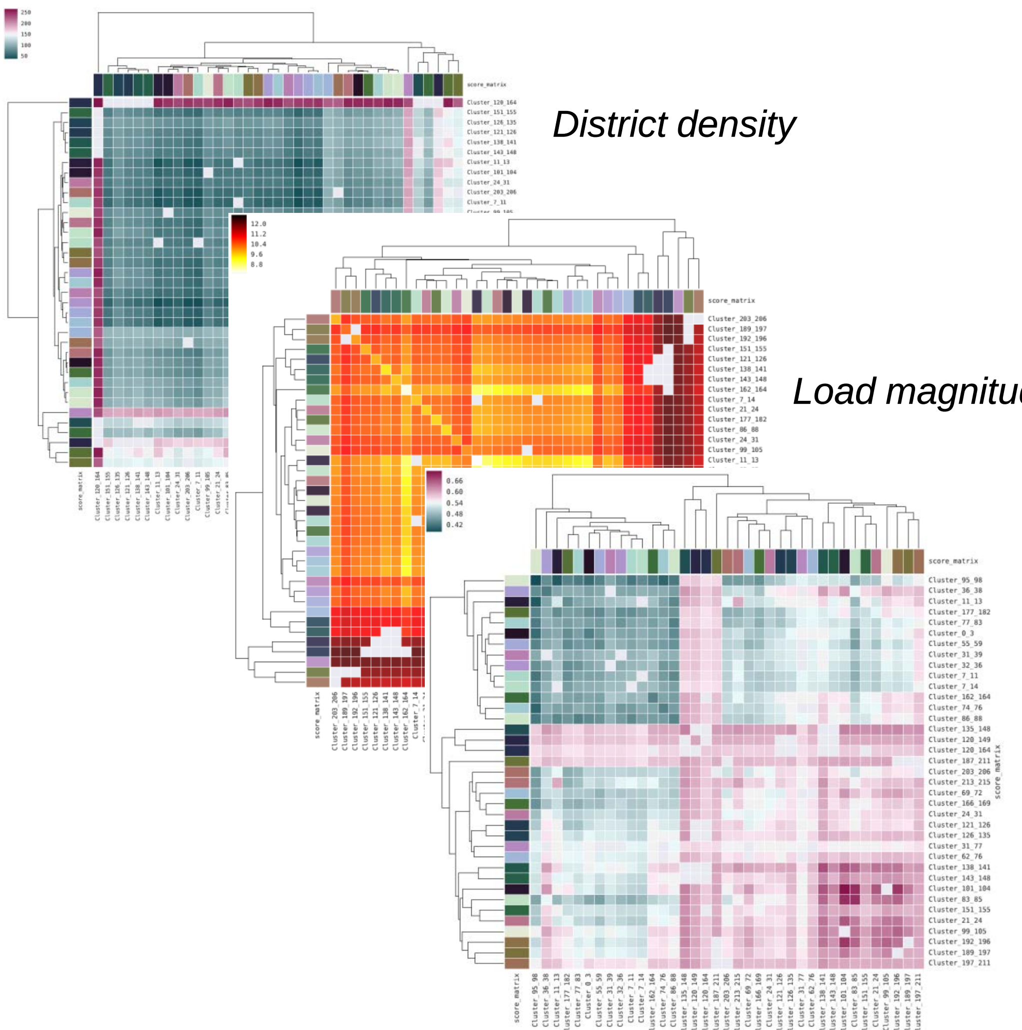
How to define clusters?

- Distance/density based
- K-means or K-medoids method

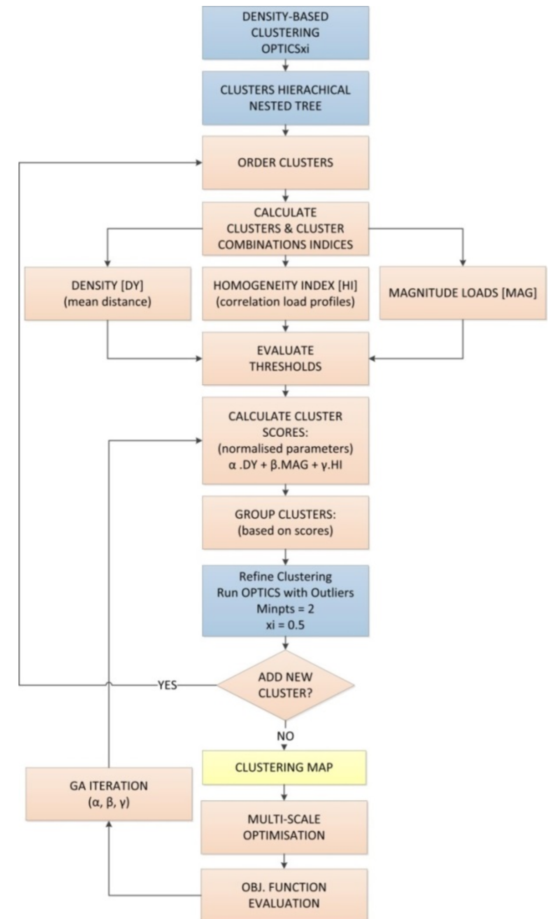
- Distance and demand based
- Locate an anchor load (i.e. Hospital)
- Set a large analysis radius, one limited by heat loss and physical boundary limitations
- Analyse the diurnal energy demands of the buildings within that radius

Improving computational efficiency - Combinatorial nested clustering

Multi-dimensional clustering of buildings



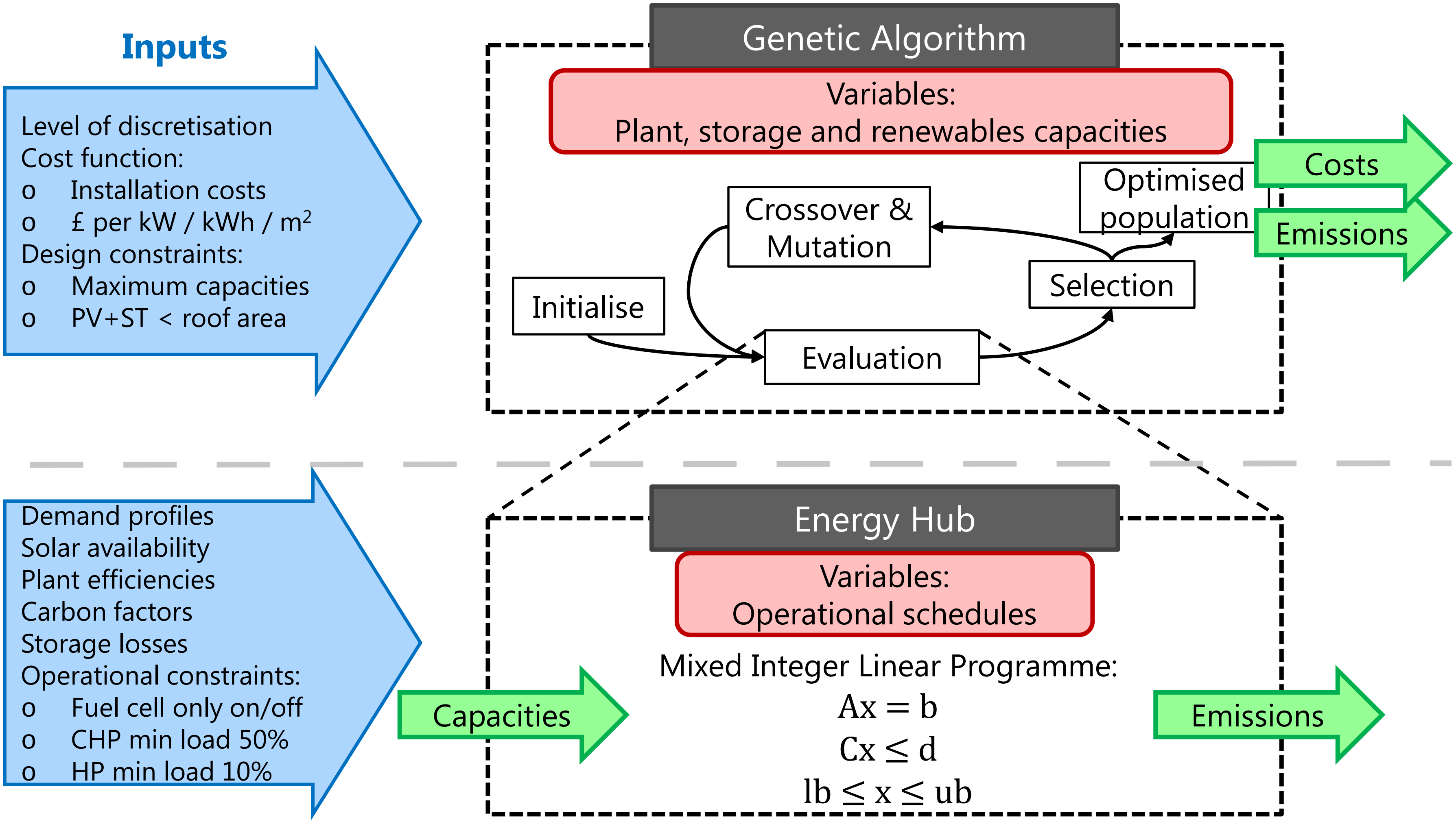
Load shifting potential



Aim: Systematically identify building clusters that effectively balance solution accuracy and efficiency

Julien F. Marquant, Ralph Evins, L. Andrew Bollinger, Jan Carmeliet (2017) A holarchic approach for multi-scale distributed energy system optimisation, Applied Energy, https://doi.org/10.1016/j.apenergy.2017.09.057.

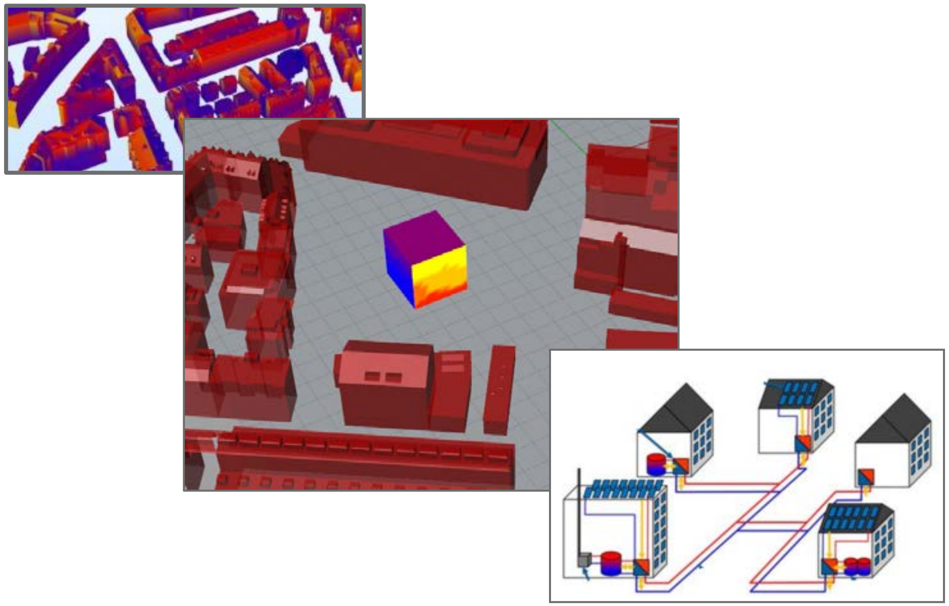
Improving computational efficiency - Bi-level optimization



Allows for solving complex problems more quickly, but optimality is not assured.

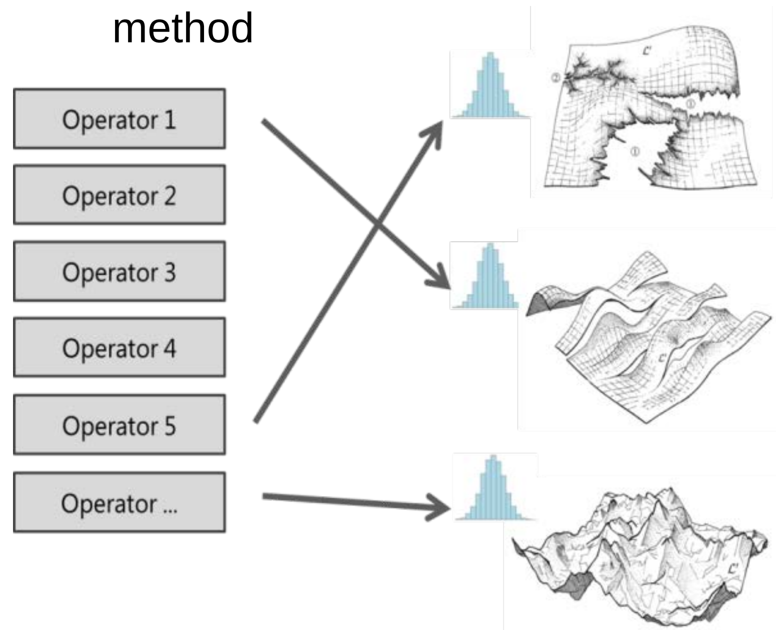
Improving computational efficiency – Hyper-heuristic optimization

- Solar potential ⇔ urban morphology
- correlation built form ⇔ energy system



Optimization of the optimization method

Solution space



- Involves tailoring your optimization algorithm to the structure of your problem
- Allows for solving highly complex problems, but no guarantee of a global optimum

Waibel C., Evins R., Carmeliet J. 2016. Holistic Optimization of Urban Morphologies and District Energy Systems. Sustainable Built Environment (SBE) regional conference, Zurich, Switzerland.

Multi-objective optimization

What's the problem?

Often you don't have a clear single optimization objective, so you need to balance amongst different objectives in optimization

- e.g. costs, CO_2 emissions, energy autonomy

What can we do?

Multi-objective optimization, either by:

1. **assigning weights to different objectives** and optimizing against the sum of the weighted objectives, or
2. optimizing against a single objective and **iteratively constraining the values** of one or more other variables (Epsilon constraint method).

Multi-objective optimization – Pareto front

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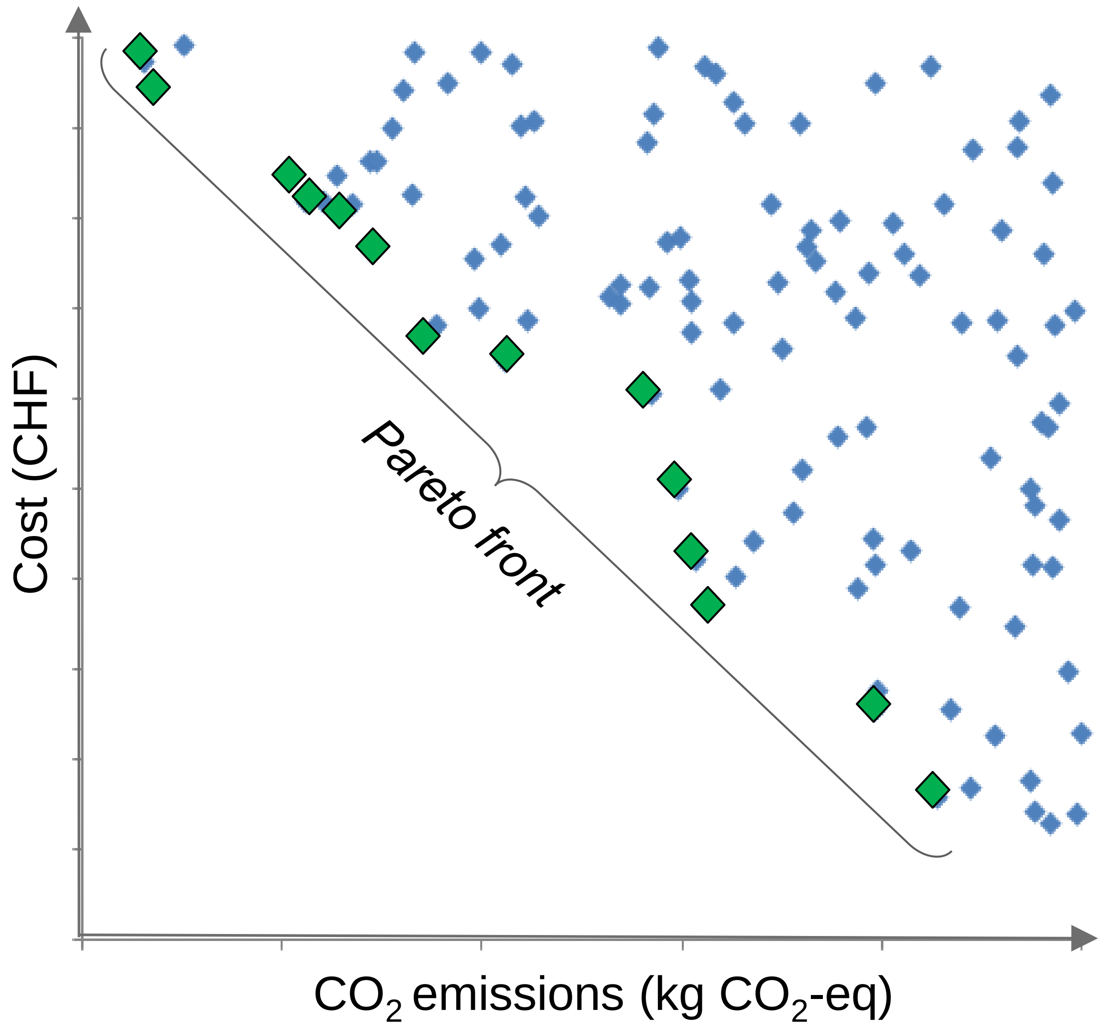
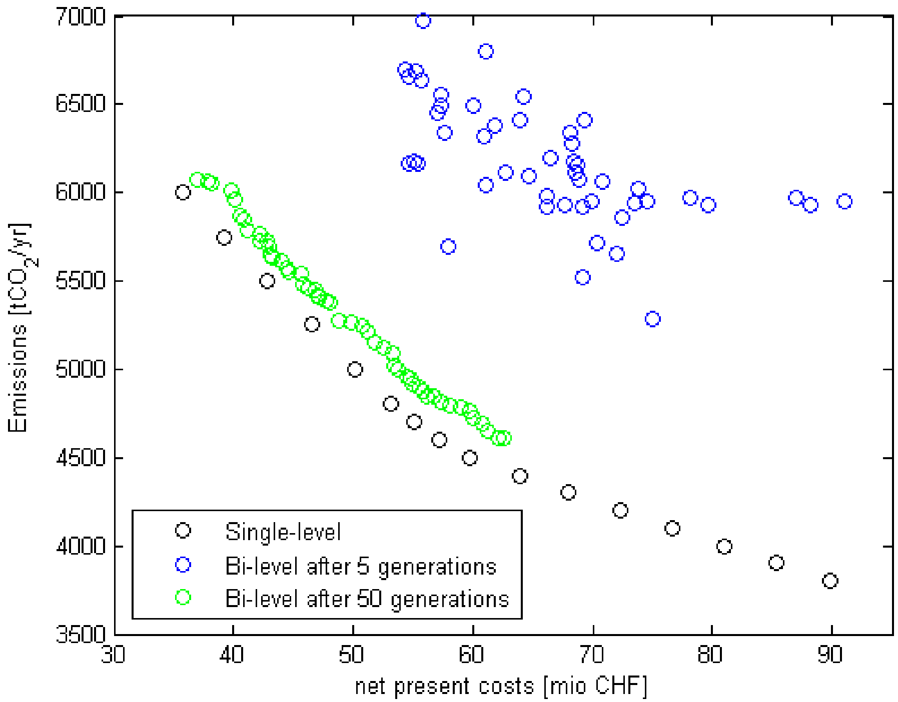
Example results from a multi-objective optimization



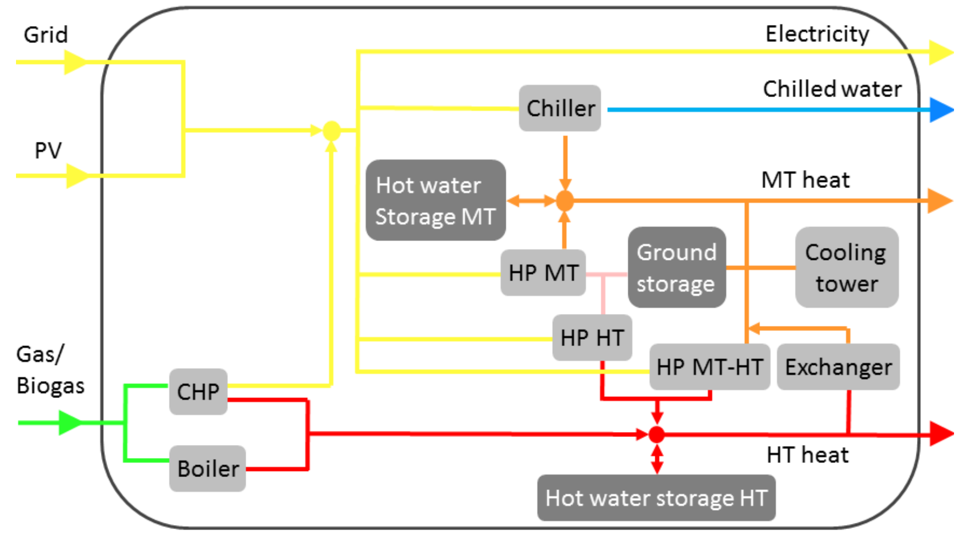
Pareto front: Set of solutions (e.g. system designs) that effectively balance different optimization objectives.

Multi-objective optimization – Example: Analysis Empa

Results: Pareto front



Energy hub as analyzed



Results: Technology capacities (kW/kWh)

Source: C. Waibel & M. Hohmann, Empa-UESL

CHP	PV [m²]	Boiler	Chiller	Cooling tower	HP MT-HT	Exchanger	HP Ground-HT	HP Ground-MT	Pump MT-Ground	Ground Storage	Heat Storage HT	Heat Storage MT	Heat Storage HT [kWh]	Heat Storage MT [kWh]	Biogas [%]	Costs [mioCHF]	Emissions [tCO2/yr]
1624	15000	909	1721	2046	0	1235	392	239	543	632	1217	184	28534	3815	100	90	3800
1621	15000	920	1721	1673	0	1033	388	238	549	625	1173	177	28215	3841	100	85	3900
1621	15000	919	1721	1554	0	963	389	238	554	626	1173	177	28130	3815	100	81	4000
1621	15000	919	1721	1553	0	962	389	238	554	626	1173	177	28132	3802	100	77	4100
1622	15000	915	1721	1484	0	915	390	239	564	629	1175	179	28028	3740	100	72	4200
1619	15000	930	1721	1162	0	517	386	232	618	618	1102	294	27122	3642	100	68	4300
1618	15000	931	1721	1146	0	301	385	232	617	617	1102	311	27120	3601	100	64	4400
1604	15000	916	1721	1099	0	53	392	264	612	612	1050	363	14091	4193	100	60	4500
1540	15000	1208	1721	1038	195	345	420	0	420	420	519	421	2524	4703	100	57	4600
1482	15000	1339	1721	1062	424	0	0	328	328	328	655	259	3206	3289	100	55	4700
1482	15000	1367	1721	1088	501	0	0	343	343	343	0	628	0	3020	100	53	4800
1454	15000	1173	1721	938	378	110	236	227	462	462	407	334	1438	2248	88	50	5000
1454	15000	1173	1721	938	378	110	236	227	462	462	407	334	1438	2248	65	46	5250
1454	15000	1173	1721	938	378	110	236	227	462	462	407	334	1438	2248	43	43	5500
1445	15000	1339	1721	1079	465	0	0	331	331	331	413	303	1486	1756	20	39	5750
1450	15000	2175	1721	1658	408	320	0	242	242	242	0	0	0	0	0	36	6000

Extending on the basic energy hub concept

1. Improving technology representation
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How can we bring these methods/techniques to practice?

Ehub Modeling Tool

An integrated tool for DES design

What?

Tool for preliminary design optimization of multi-energy systems for districts and communities.

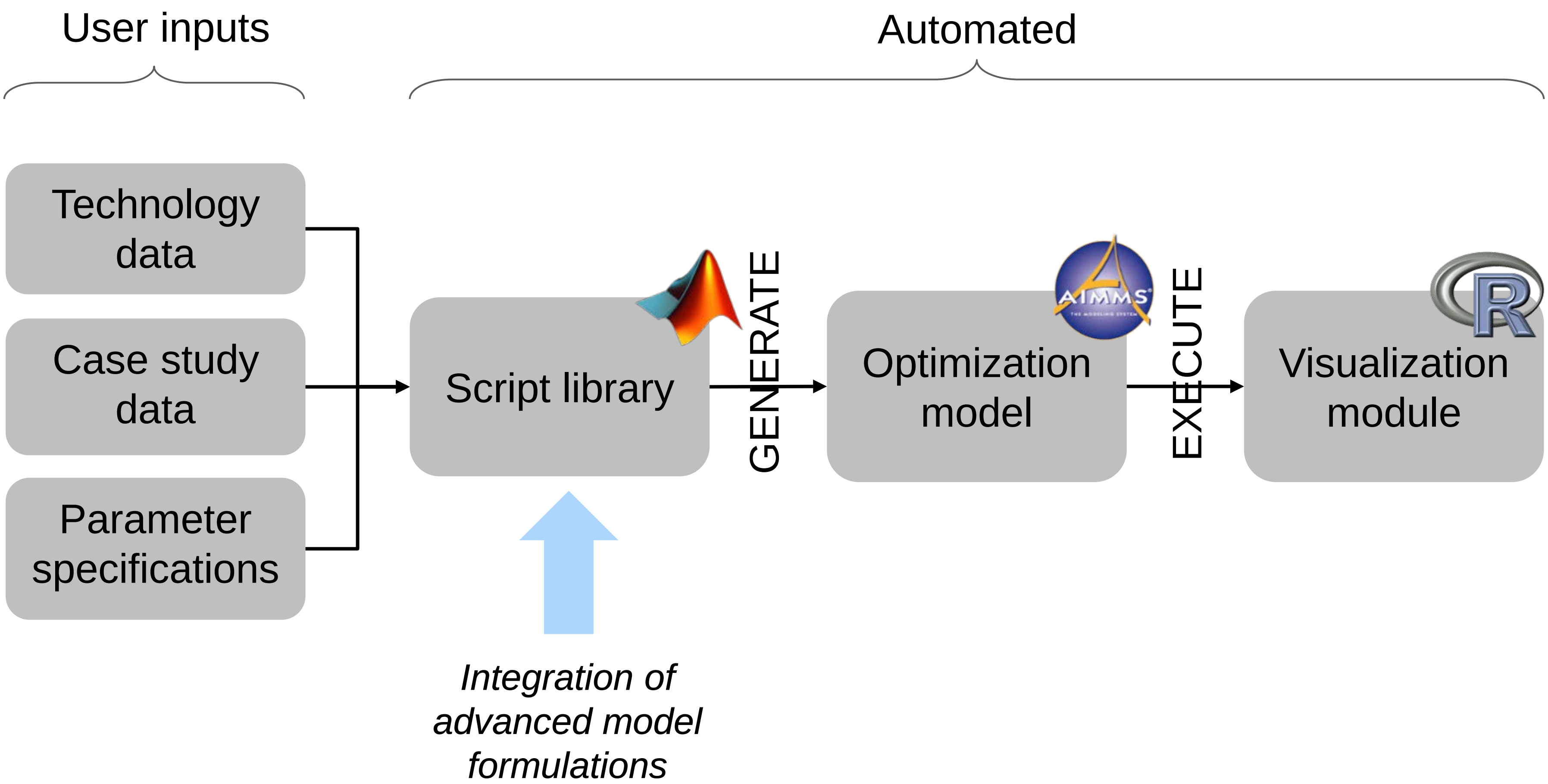
Why?

1. Enables integration of energy hub modeling innovations (e.g. uncertainty analysis, network optimization, etc.) into a common framework.
2. Significantly reduces the effort and time required for implementing advanced analyses.

Where?

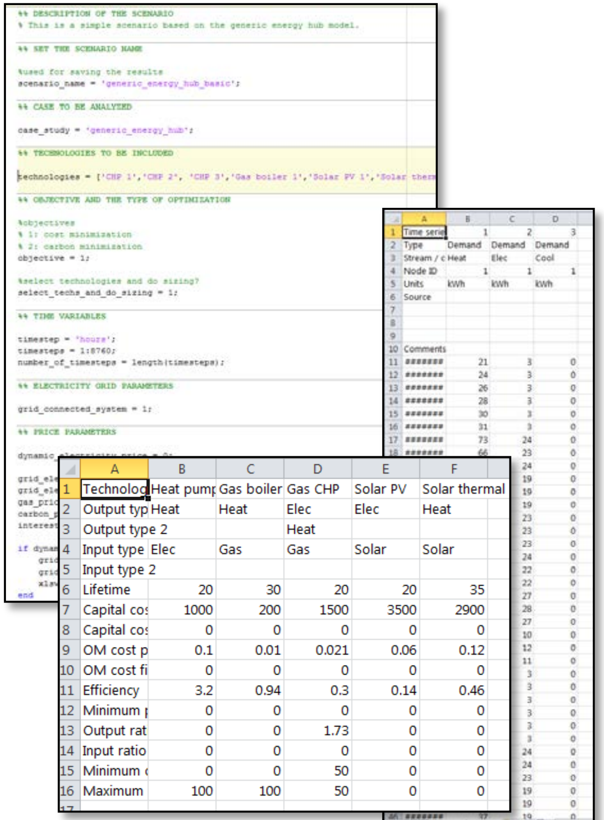
- https://github.com/hues-platform/ehub-modeling-tool
- https://github.com/hues-platform/python-ehub

Ehub Modeling Tool – Software workflow



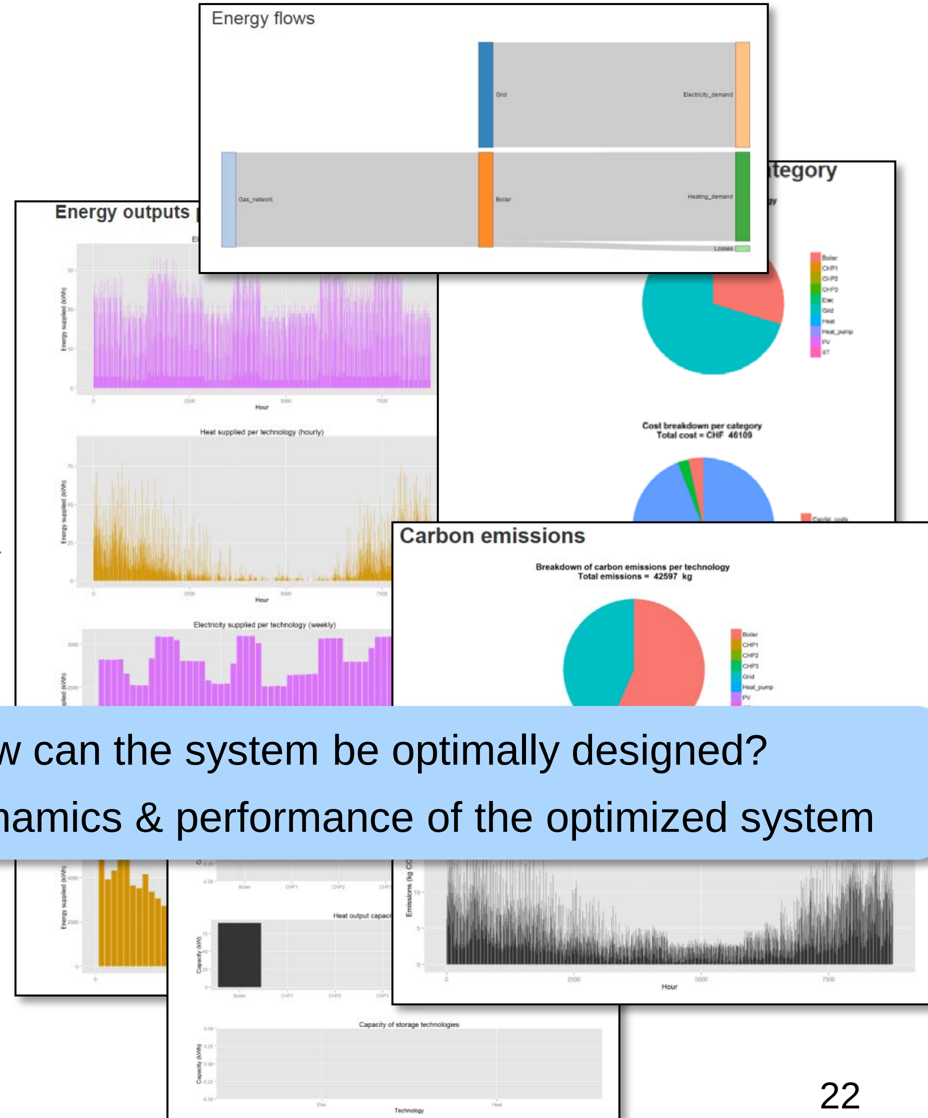
Ehub Modeling Tool - Workflow

Experiment definition



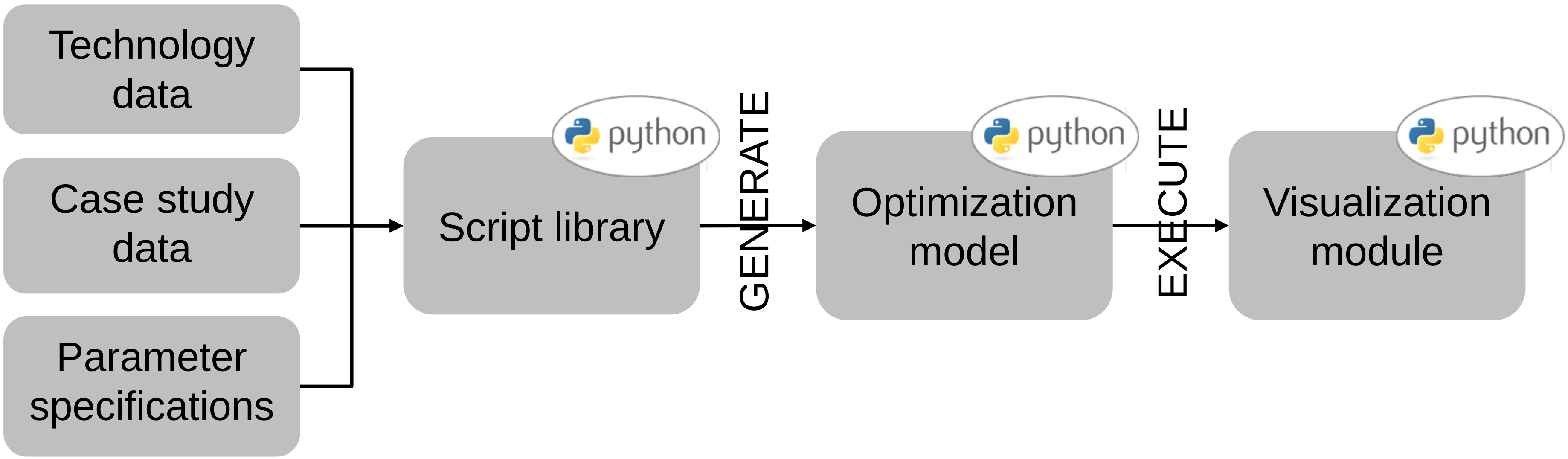
Run

Visualizations/reports



1. How can the system be optimally designed?
2. Dynamics & performance of the optimized system

Current work: Open source implementation



Python-ehub tool:

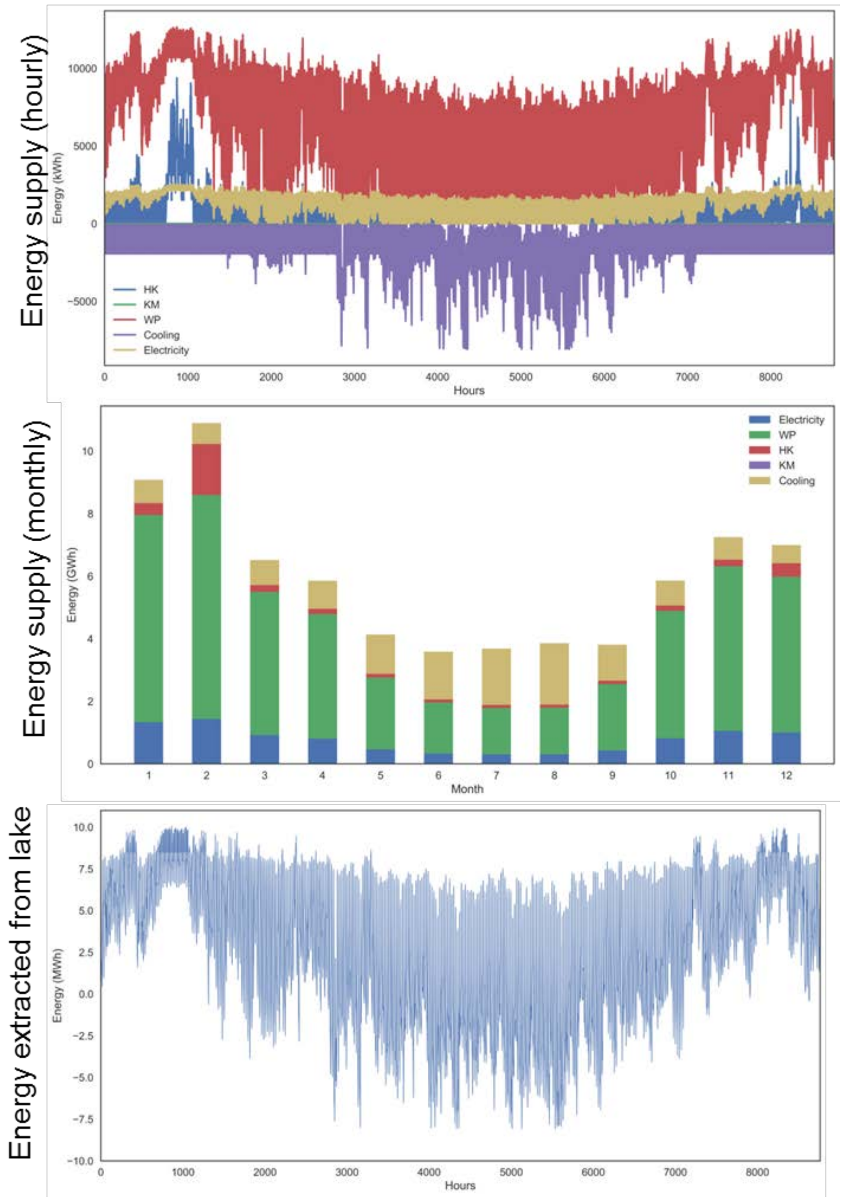
- Open source tool chain
- More unified development environment
- Collaborative & distributed development

The Ehub Modeling Tool in practice

Lengg Case (Helbling):

- Study of design options for a seawater-based thermal network in the Lengg area of Zurich.
- Capabilities of Python-ehub tool expanded to address the knowledge needs of Helbling (additional constraints, data outputs)
- Results compared with calculations by Helbling

Results variant 1



Summary

1. **Advanced model formulations** are essential to the application of energy hub modeling in real-world situations.

2. The implementation of advanced model formulations is knowledge intensive - **automated model development** is critical for their implementation in practice.

3. The **Ehub Modelling Tool** is a starting point for this.

Thank you for your attention.

https://hues-platform.github.io

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