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and Energy

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by the German Bundestag

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Benefits of Decomposition Methods to Speed-up Energy System Modelling and Application to Stochastic Optimization

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Prague, 21.09.2016

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   - The problem of uncertainty in Energy System Modelling
2. Current implementation of stochastic optimization
   - From deterministic to stochastic modelling
   - Improving convergence by Enhanced Benders approaches
3. Challenges and possible improvements
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   - Application to path optimization

The problem of uncertainty in Energy System Modelling

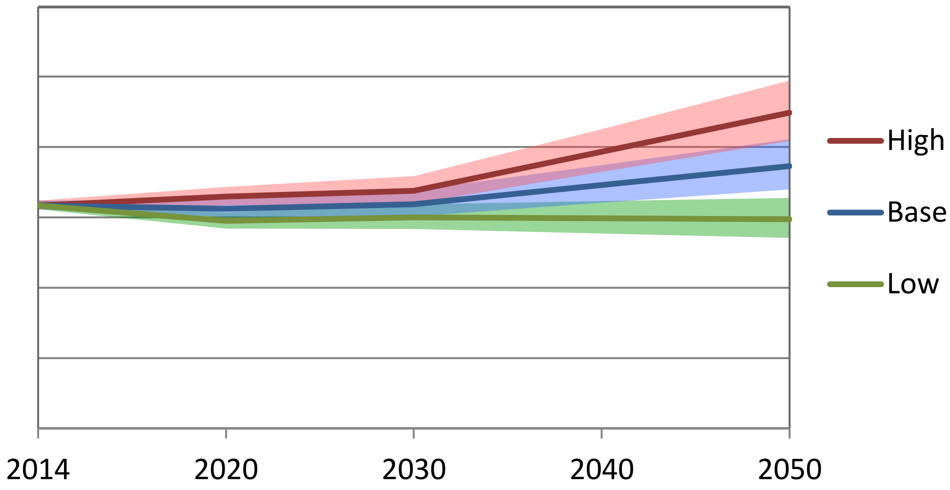
The problem of uncertainty in energy system modelling

Robust scenario High
- ↑ Sensitivity analysis
- ○ Model result High
- ↓ Sensitivity analysis

Robust scenario Base
- ↑ Sensitivity analysis
- ○ Model result Base
- ↓ Sensitivity analysis

Robust scenario Low
- ↑ Sensitivity analysis
- ○ Model result Low
- ↓ Sensitivity analysis

Path development of an uncertain parameter



- Long term capacity expansion planning requires **making decisions now**, which have an impact on the energy system for several decades.
- **Context scenarios** can give a general direction of development, however a large number of **consistent sub-scenarios** are possible. The current approach usually considers only the main scenario and evaluates robustness by sensitivity analysis of sub scenarios.

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Benders decomposition for two-stage stochastic optimization

(L-shaped Method)

[Benders 1962 and Van Slyke 1969]

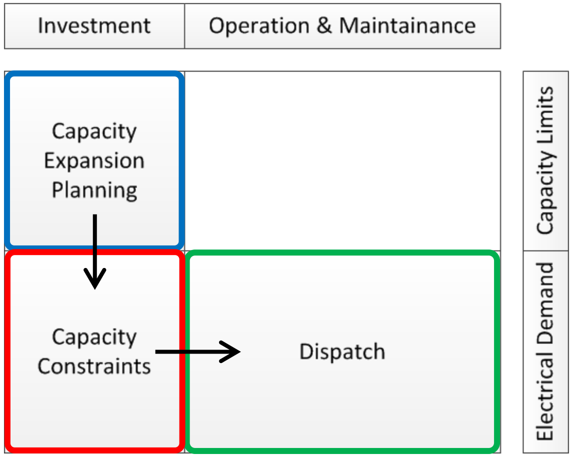
Master problem:

- **Decide now** which capacities should be expanded

Sub problem:

- **Decide later** on economic dispatch to satisfy electrical demand with capacities given by master problem

Mathematical formulation in LP table



1st Stage:
Capacity expansion – Installed capacities

2nd Stage:
Dispatch – Generation variables

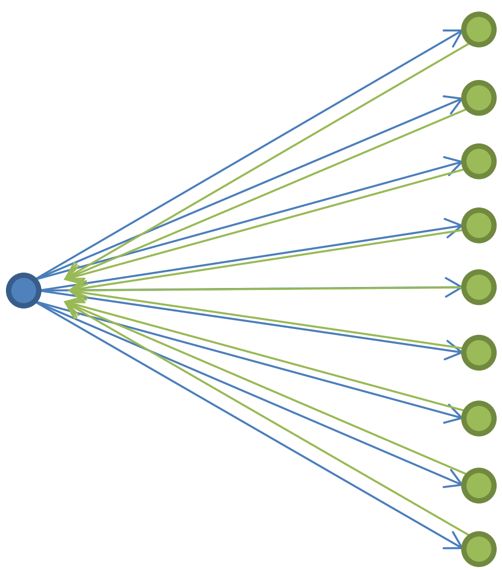
Linking variables:
Installed capacities, connecting the capacity expansion problem and the dispatch problem

Benders decomposition separating capacity expansion planning and economic dispatch

1. Two-stage decision tree

Stage 1
(Master problem)
Investment decision

Stage 2
(Sub problem)
Stochastic economic dispatch scenarios



Investment

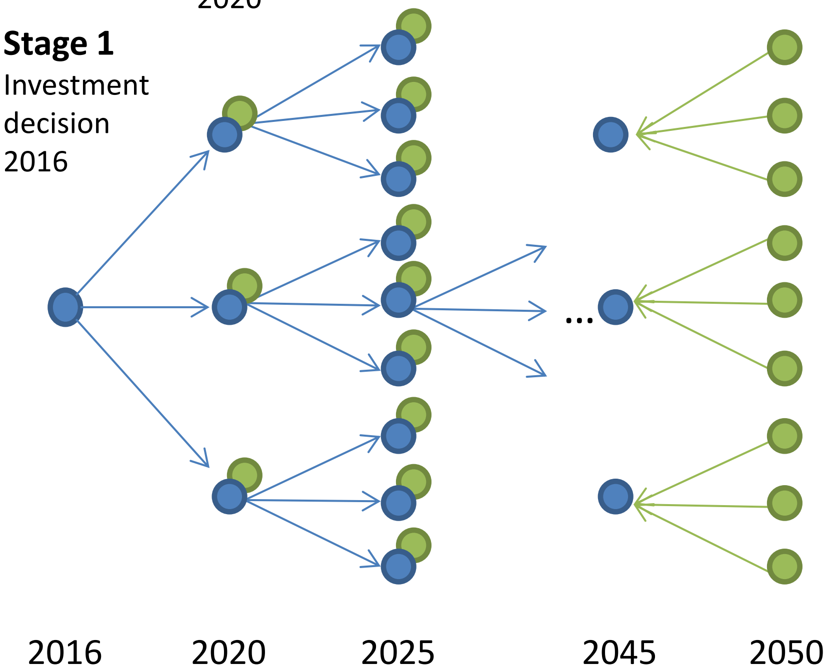
Dispatch

2. Multi-stage decision tree

Stage 1
Investment decision 2016

Stage 2
Dispatch & Investment decision 2020

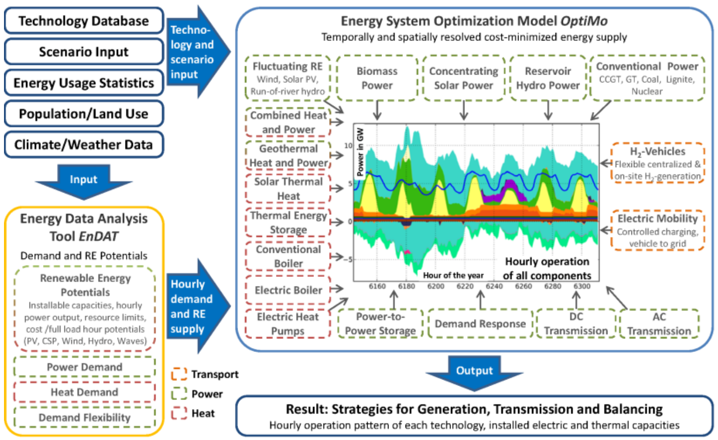
Stage 3
Dispatch & Investment decision 2025



Current implementation of stochastic programming

The REMix Model

REMix



- Capacity expansion planning and economic dispatch
- **High** spatial, temporal and technological **resolution**
- **Modular approach** to include heat sector, electromobility, DSM and others

GAMS SIMPLE

- **Simplified version** of REMix, used as a development platform
- **Scalability** of model dimensions by generic data generation
- ➢ Modified for demonstrating implementation approaches for stochastic optimization

Implementation of Enhanced Benders decomposition approaches

GAMS Simple Model:
- Capacity expansion planning and economic dispatch

1. Implementation of a Benders decomposition approach
Seperating capacity expansion and economic dispatch

Deterministic version of
The GAMS SIMPLE model

Master problem:
Investment decision

Sub problem:
Economic dispatch

Suggested solution

Capacities for installed plant capacities, electric storages and links for each region

Optimality Cut

Information about the marginals of the first stage decision variables

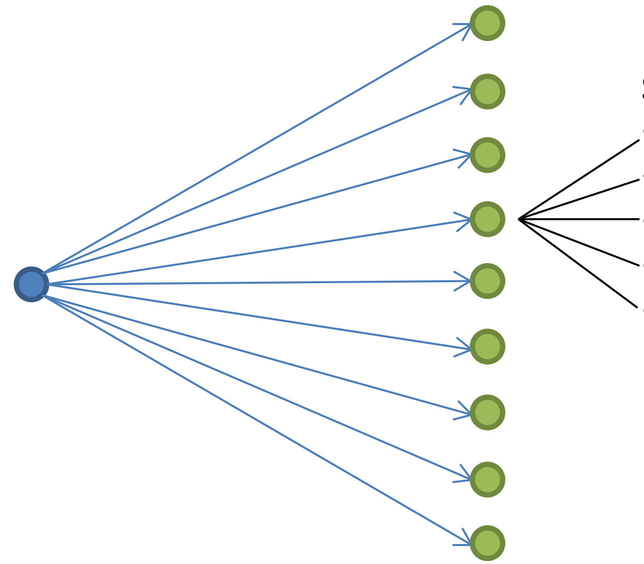
Implementation of Enhanced Benders decomposition approaches

1. Implementation of a Benders decomposition approach
Seperate regions and type

2. Stochastic model with scenarios
- Each scenario has a probability
- Stochastic model is still single threat

Master problem:
Investment decision

Sub problem:
Economic dispatch scenarios



Set of uncertain parameters
- Electrical demand
- Fuel prices
- Wind time series
- Solar time series
- E-mobility usage

- Each subproblem is weighted by a probability and represents a specific set of assumptions for uncertain parameters

Implementation of Enhanced Benders decomposition approaches

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2. Stochastic model with scenarios

3. Simple Computing
- Scenarios are processed one after another

4. Grid computing
- Scenarios and parts of the modell can be placed in several threats

5. Deterministic Model
- One modell for master and subproblem

Testing with
Model nodes: 3
Scenarios: 100
<< 3-4 GB RAM

Testing with
Model nodes: 3
Scenarios: 100
= 3-4 GB RAM

Testing with
Model nodes: 3
Scenarios: 100
= 40 GB RAM

- **Small ESM** with 3 power plants, 3 storages, 2 node links and 8760h
- Formulation as Deterministic Equivalent for small problems faster than Benders decomposition, but leads to **memory restrictions** in large models

Implementation of Enhanced Benders decomposition approaches

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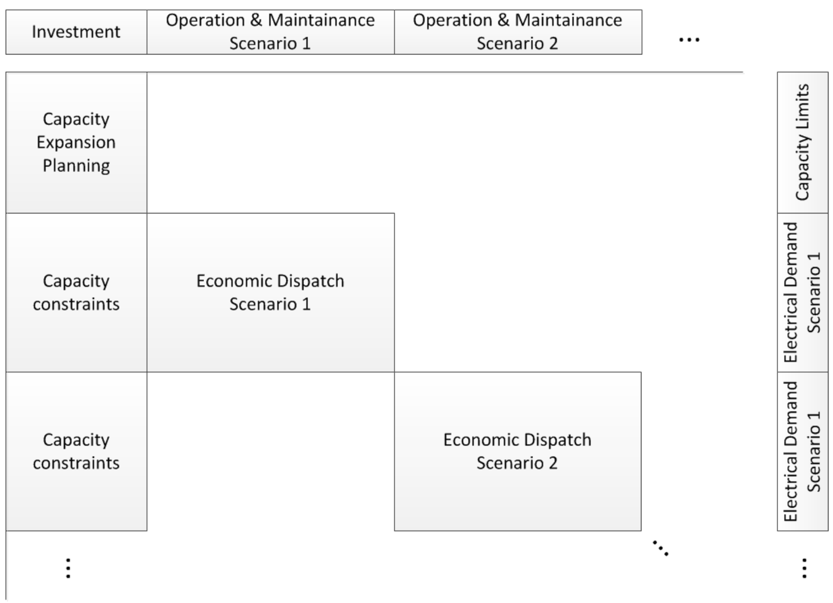
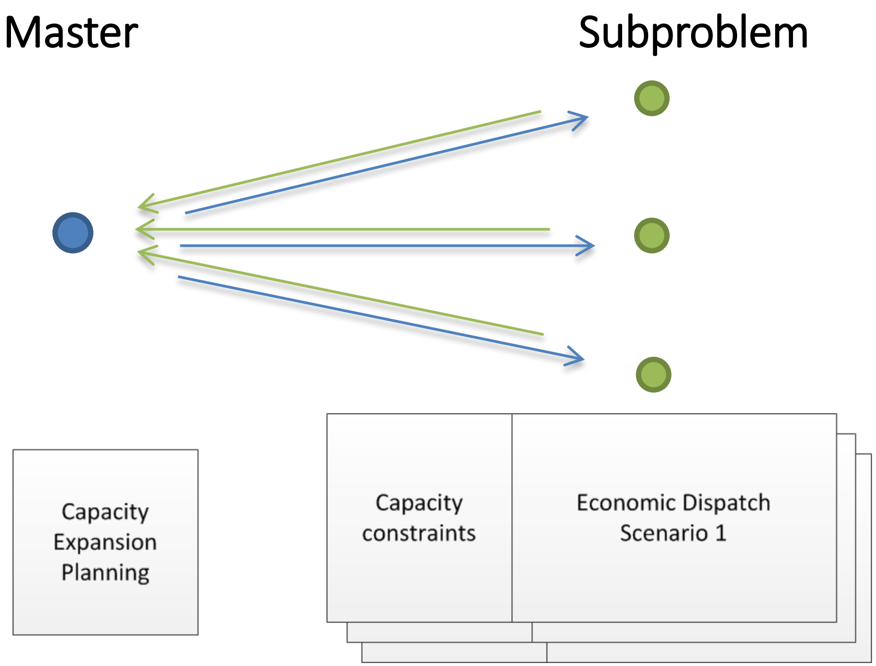
Deterministic Equivalent



- Size of LP increases with number of scenarios, solved by SIMPLEX / Barrier
- **Out of memory** for typical REMix problems with scenario dimension

Benders Decomposition



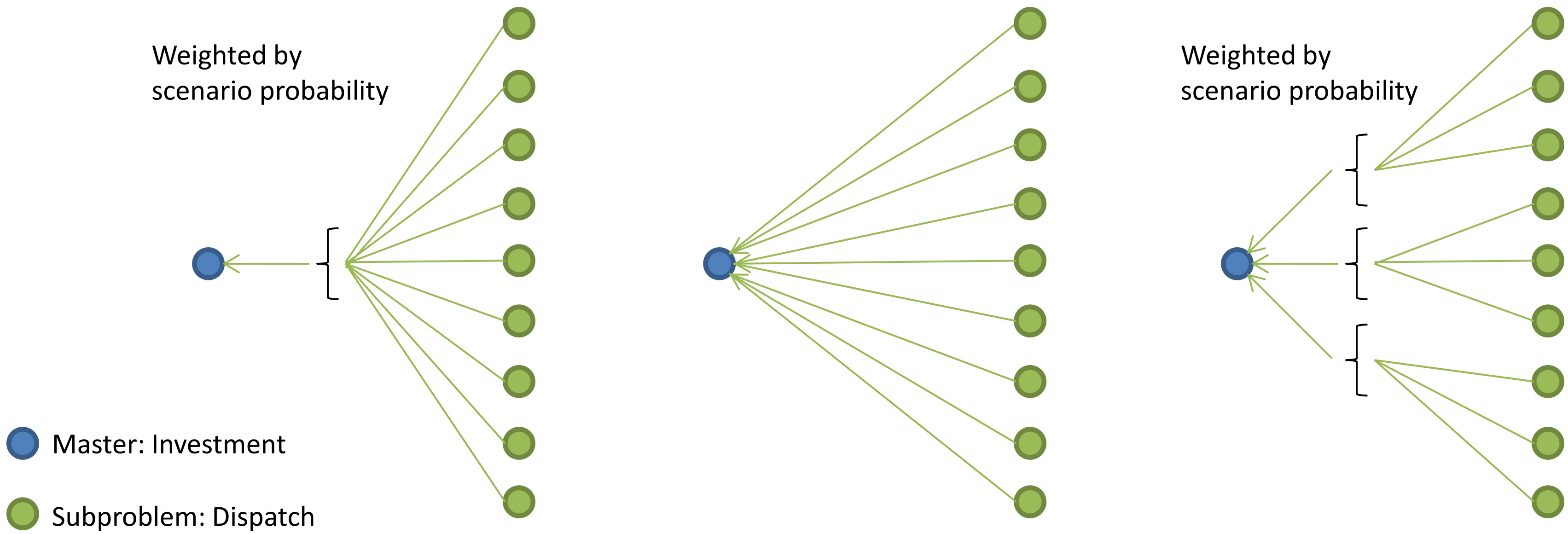
- Subproblems can be **solved in parallel**
- Memory demand **scales** with number of parallel solve processes

Improvement by optimality cut type

Singlecut
- One optimality cut per iteration is submitted to master problem

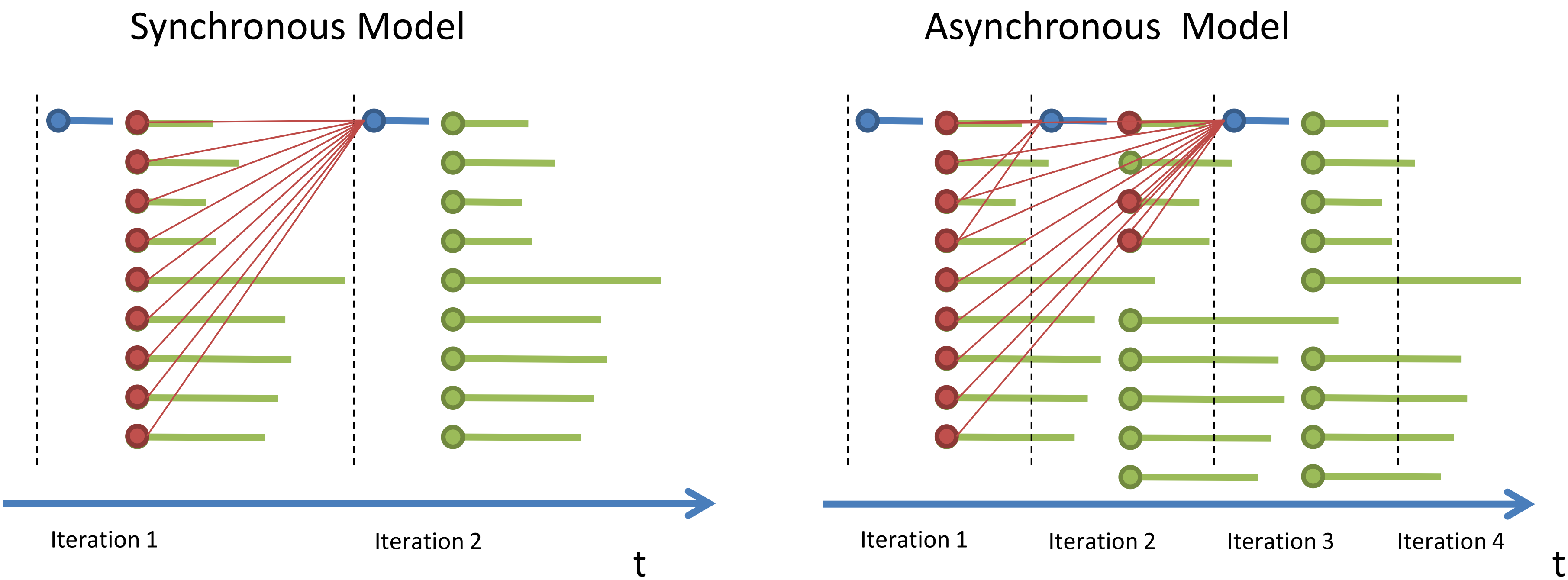
Multicut
- Each subscenario submits an optimality cut each iteration

Clustercut
- Each cluster submits an optimality cut each iteration



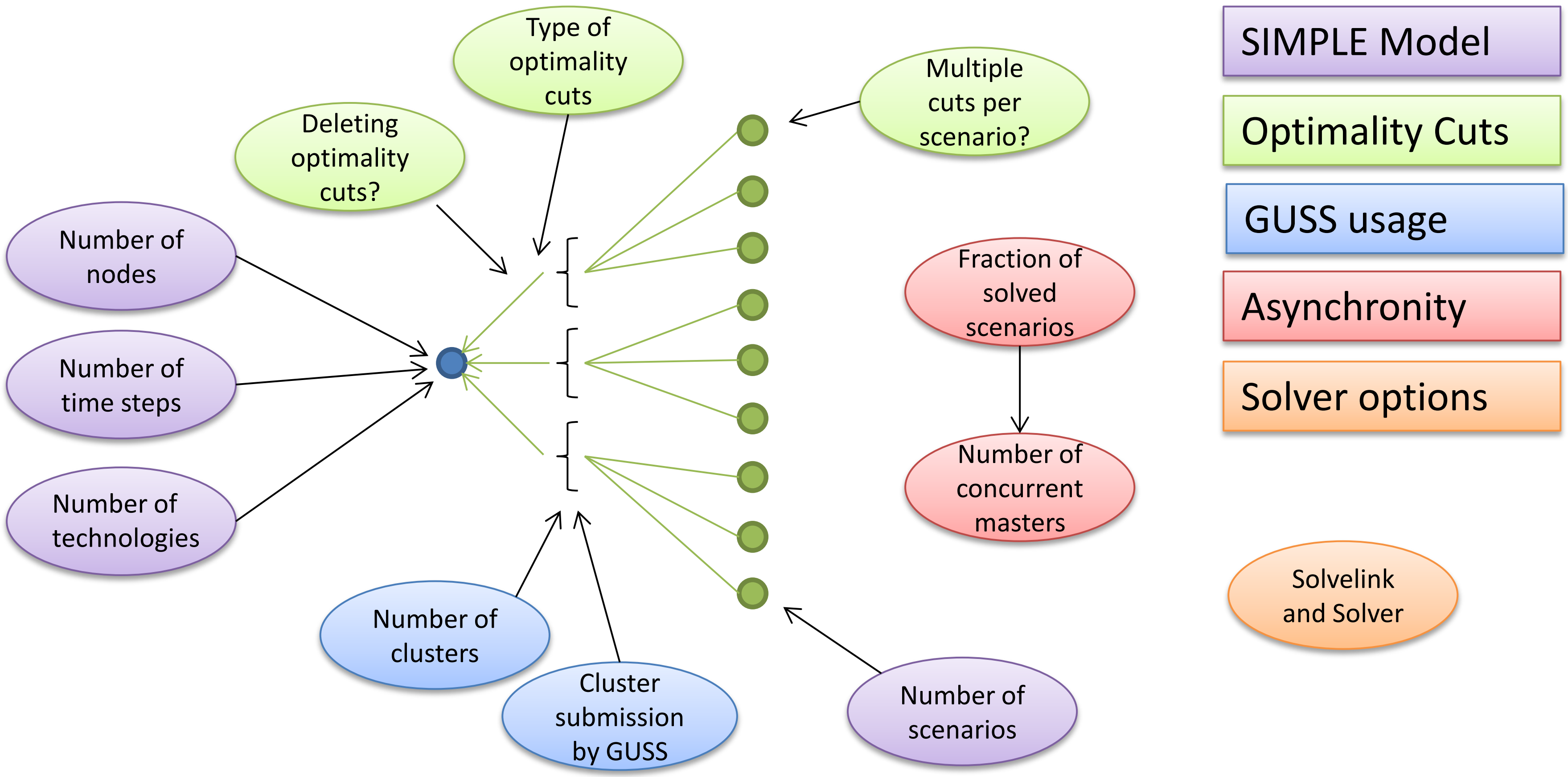
- Multicuts give **detailed information** but increase complexity [Birge 1988]
- Singlecuts **aggregate information** therefore more iterations are necessary
- Dynamic switching between cut-types is possible [Skar 2014]

Improvement to achieve asychronity



- New Master can be started as soon as a **fraction of scenarios are solved**, new iteration has only **partial information** therefore the number of iterations increases [Linderoth 2003]
- Trade-off between more iterations and parallelisation

Algorithm parameters



- Large number of parameters to optimize performance of Enhanced Benders Algorithm making **systematic testing necessary**

Computational test results

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Method	Clustercut	Multicut	Multicut + TR	MC + TR + GUSS
Iterations	138	77	54	61
Time to solve	5:54 h	4:42 h	3:14 h	2:51 h
CPU load max	300 %	449 %	466 %	134 %
CPU load avg.	66.9 %	70.8 %	56.2 %	18.6 %
RAM usage max	0.58 GB	0.58 GB	0.48 GB	0.67 GB
RAM usage avg.	0.11 GB	0.16 GB	0.11 GB	0.26 GB

- Model building time **limiting constraint**, models are solved faster than generated therefore low average CPU load (100 % equals 1 core out of 32)
- Exchange of information between GAMS and solver can be accelerated by using **shared memory** and running GAMS and CPLEX in **different threads**, this comes at the cost of increased memory demand

Challenges and possible improvements

Challenges

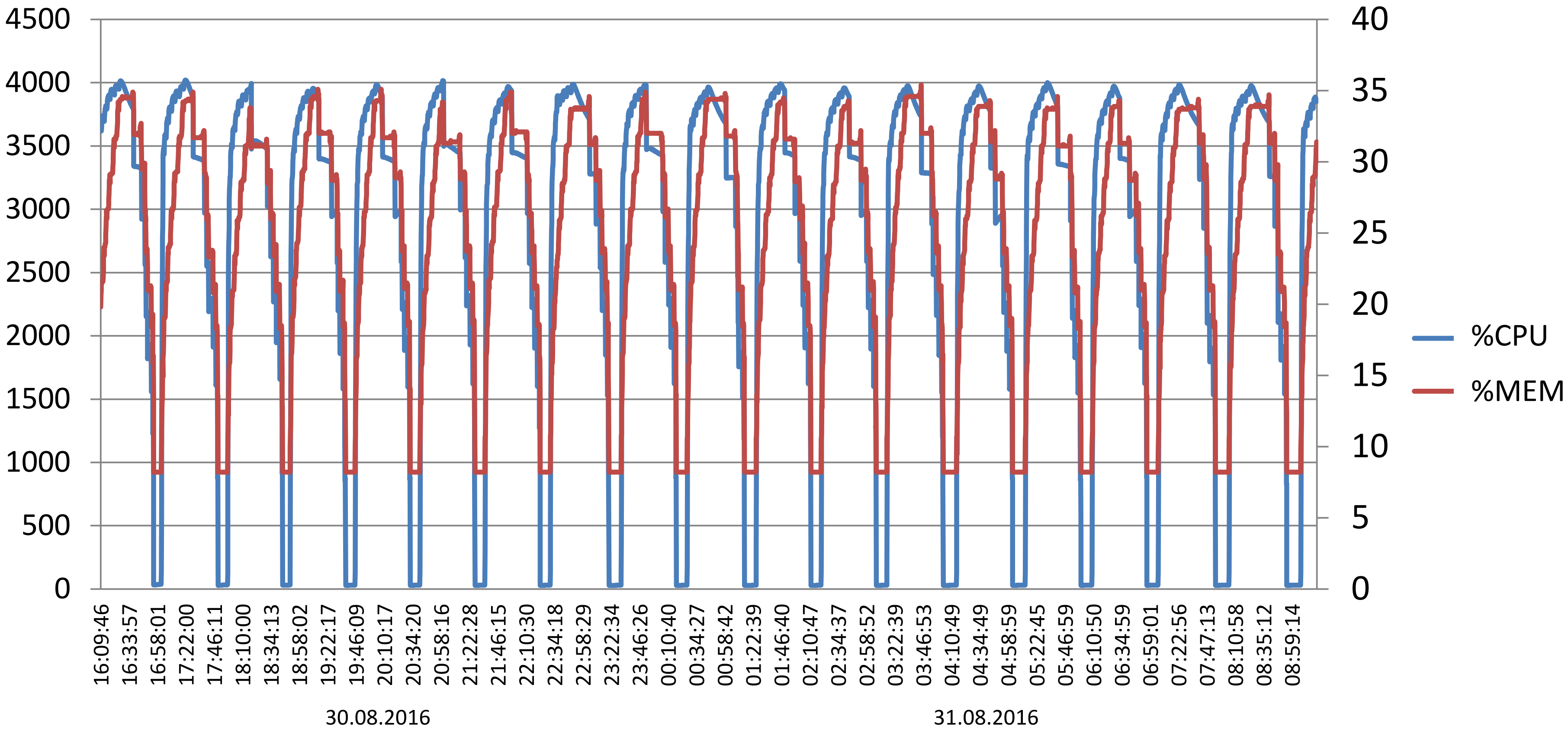
- **Reducing computational overhead** by using methods which simplify or reduce model building time (Usage of GUSS, externalizing model building)
- **Balancing CPU load** for migration to high performance computing

- **Generating better cuts** - insufficient electrical generation will cause all plant types in a region to be built
- **Deleting unused cuts** in order to keep the masterproblem as small as possible while retaining important information

- **Improving the starting point** for the Trust-Region approach

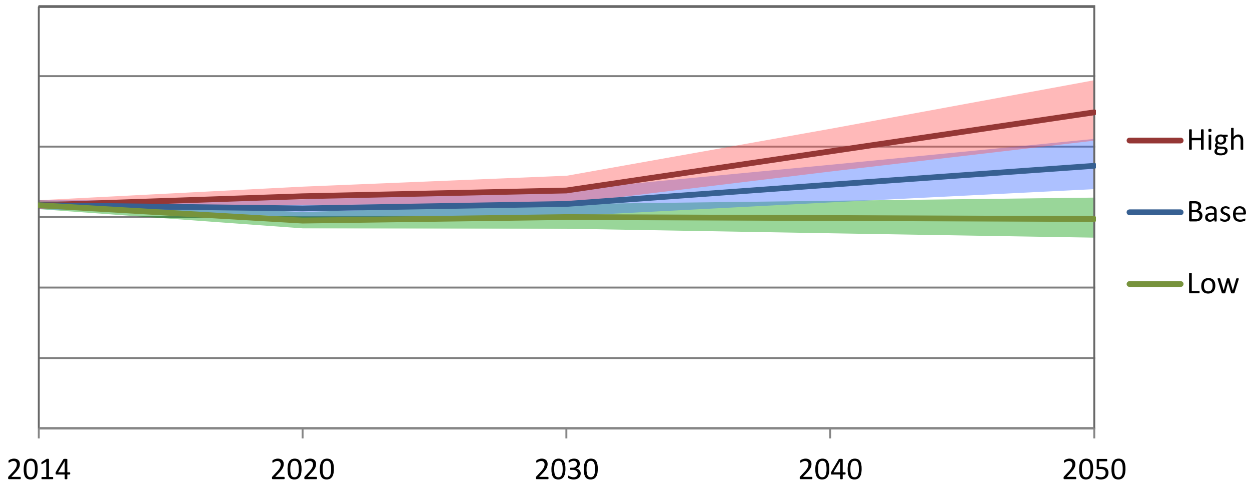
- Combining stochastic optimization with **decomposition on the scenario level** (decoposition in model nodes or timesteps) in a Nested Benders approach

Challenges

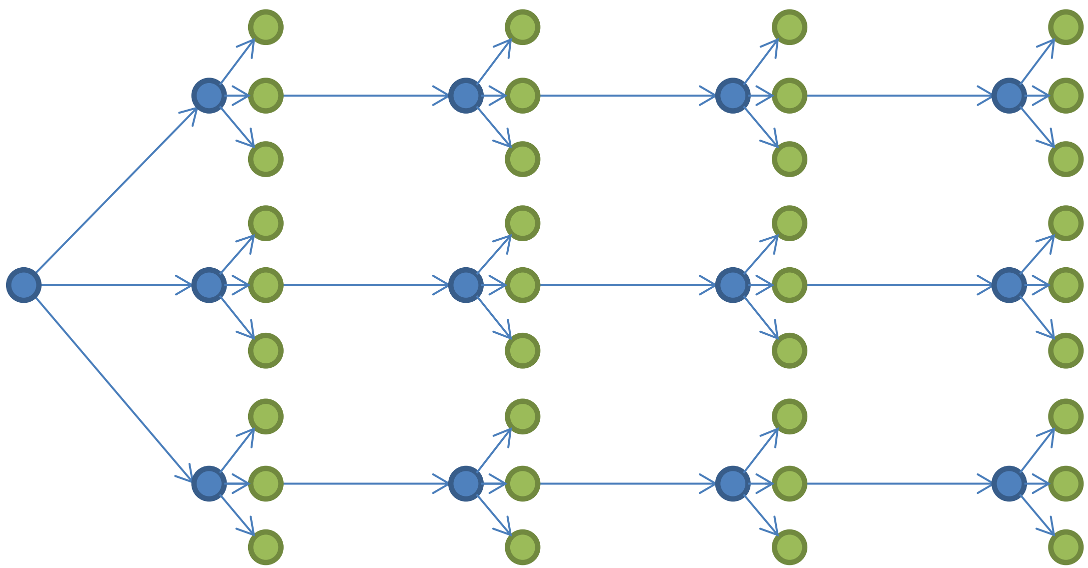


- Large scale scenario with typical **synchronous behavior**
- Gaps indicate solving master while peaks represent parallel subproblems
- High correlation between CPU and memory load indicating scalability with number of parallel processes

Application to path optimization



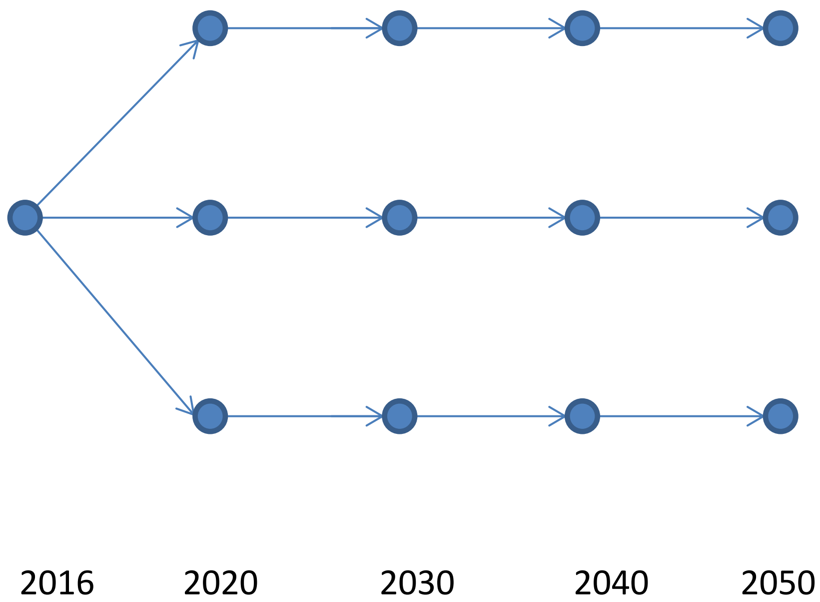
Motivating example from introduction



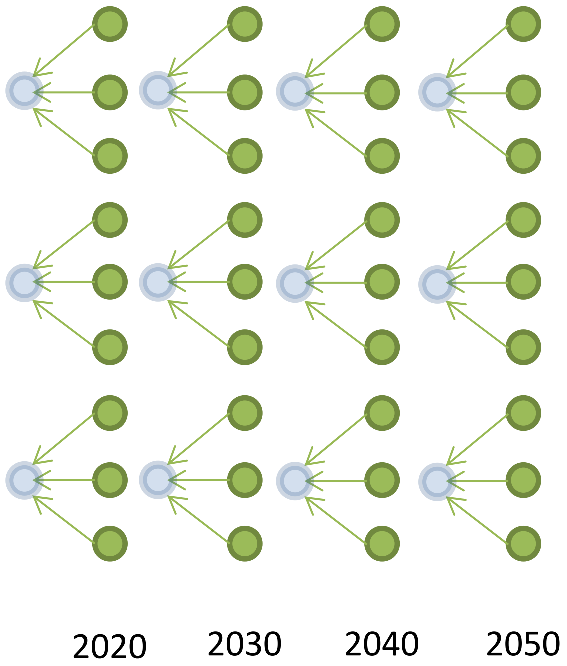
Result:
3 Context scenario pathways including 3 subscenarios each

Application to path optimization

Masterproblem



Subproblems



- Application of Benders decomposition in capacity expansion planning and economic dispatch leads to a **large number of subproblems** which can be **solved in parallel**

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