Multistage grid investments incorporating uncertainty in Offshore wind deployment

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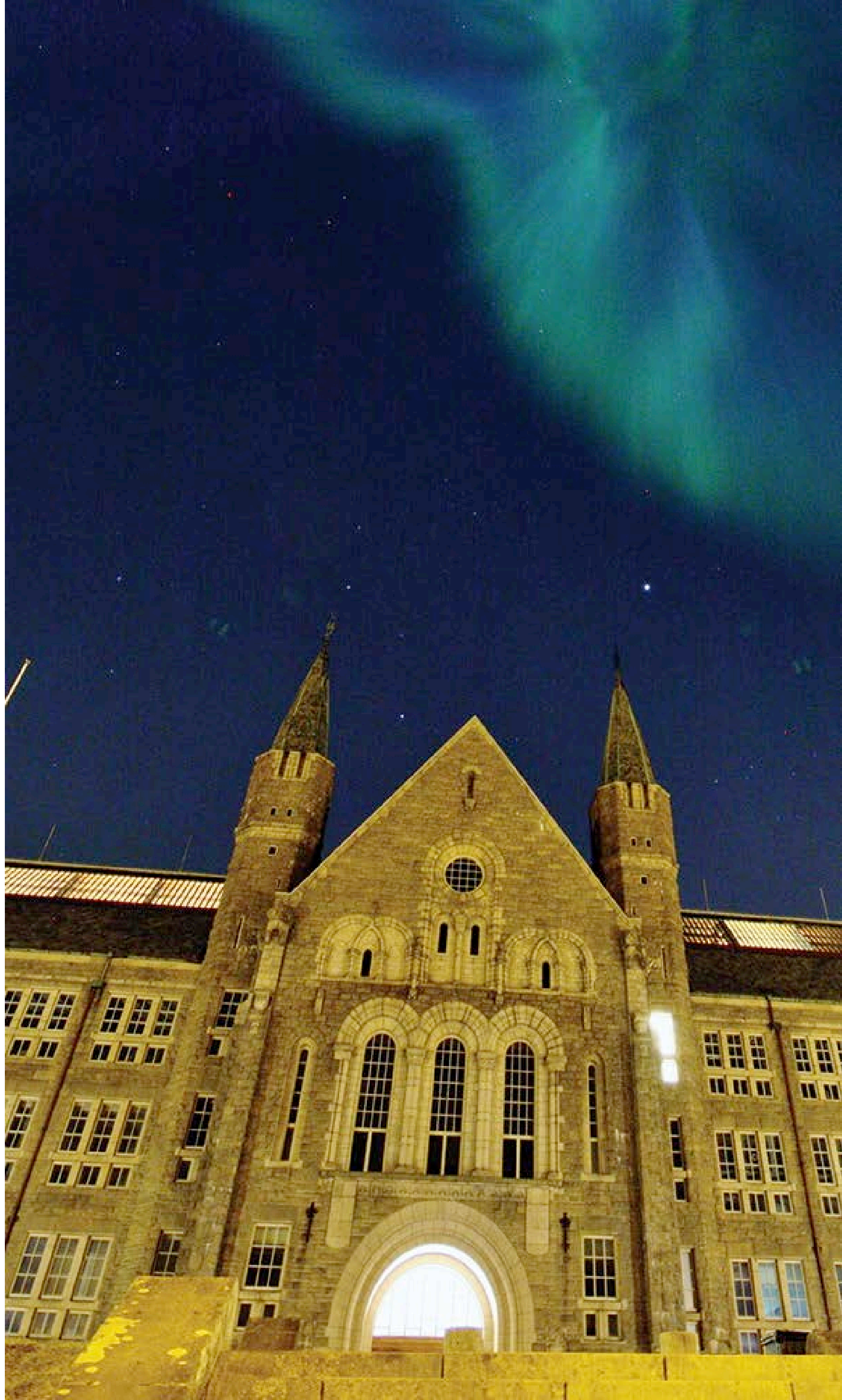
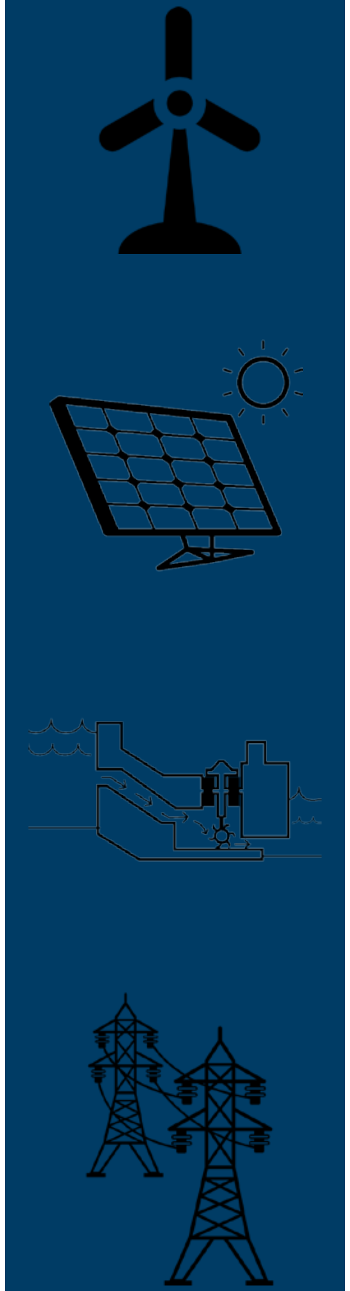
Content

- Transmission expansion planning model
- Incorporating uncertainty in offshore wind deployment
- North Sea 2030 case study



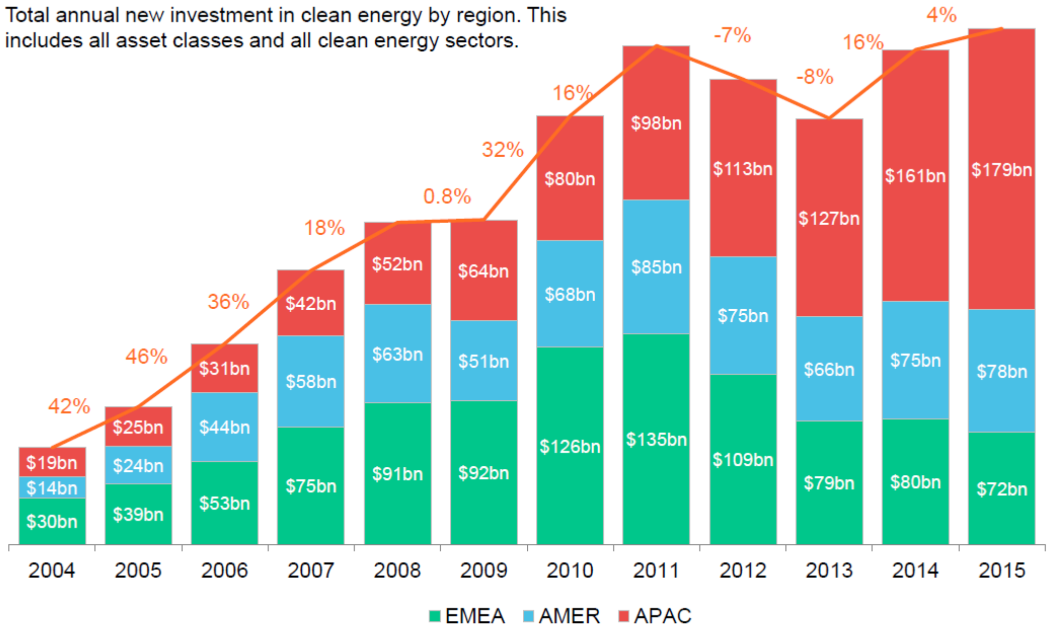


Background

Investment levels in renewables

Annual Investments by Region

- Total annual new investment in clean energy by region. This includes all asset classes and all clean energy sectors.

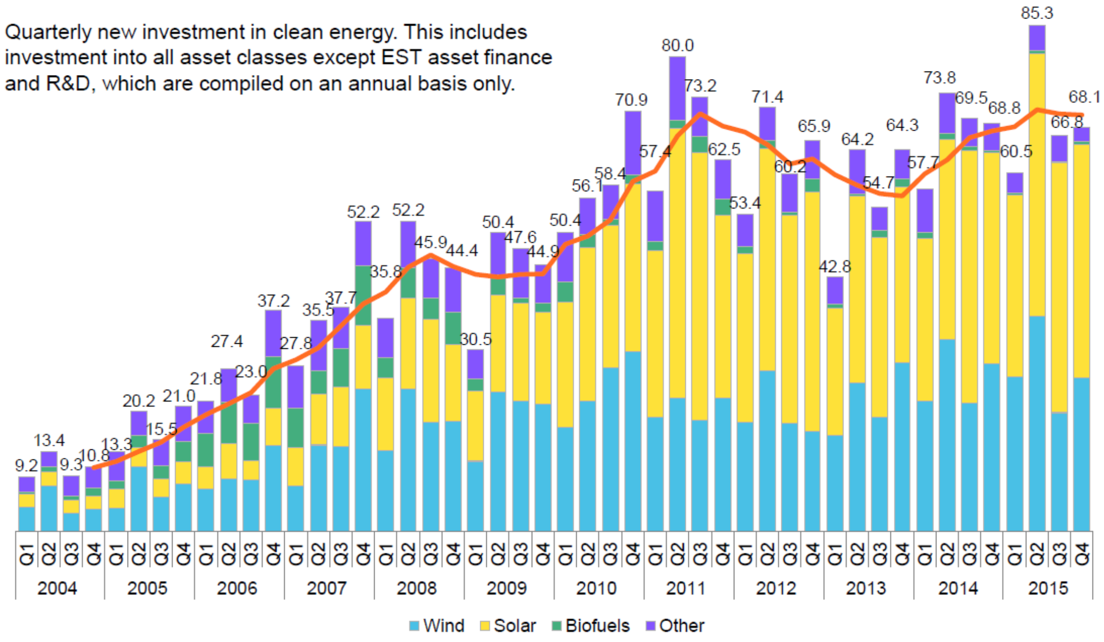


Note: Total values include estimates for undisclosed deals. Includes corporate and government R&D, and spending for digital energy and energy storage projects (not reported in quarterly statistics).

Source: Bloomberg New Energy Finance

Quarterly Investments by Assets (ex. R&D)

- Quarterly new investment in clean energy. This includes investment into all asset classes except EST asset finance and R&D, which are compiled on an annual basis only.



Note: Total values include estimates for undisclosed deals. Excludes corporate and government R&D, and spending for digital energy and energy storage projects (reported in annual statistics only).

Source: Bloomberg New Energy Finance

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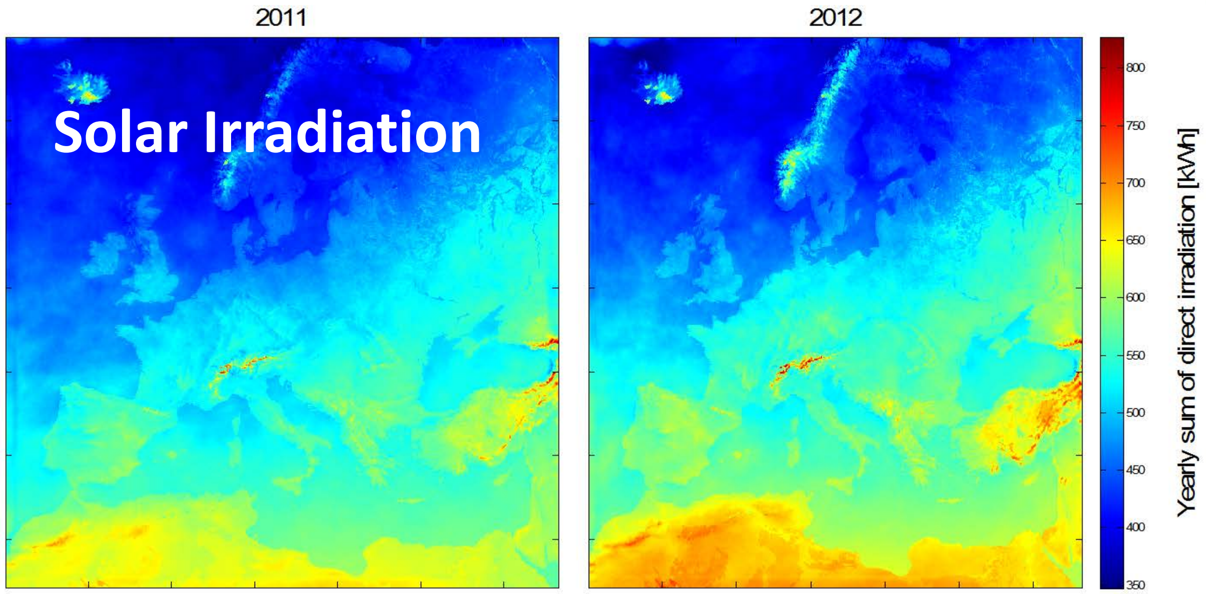
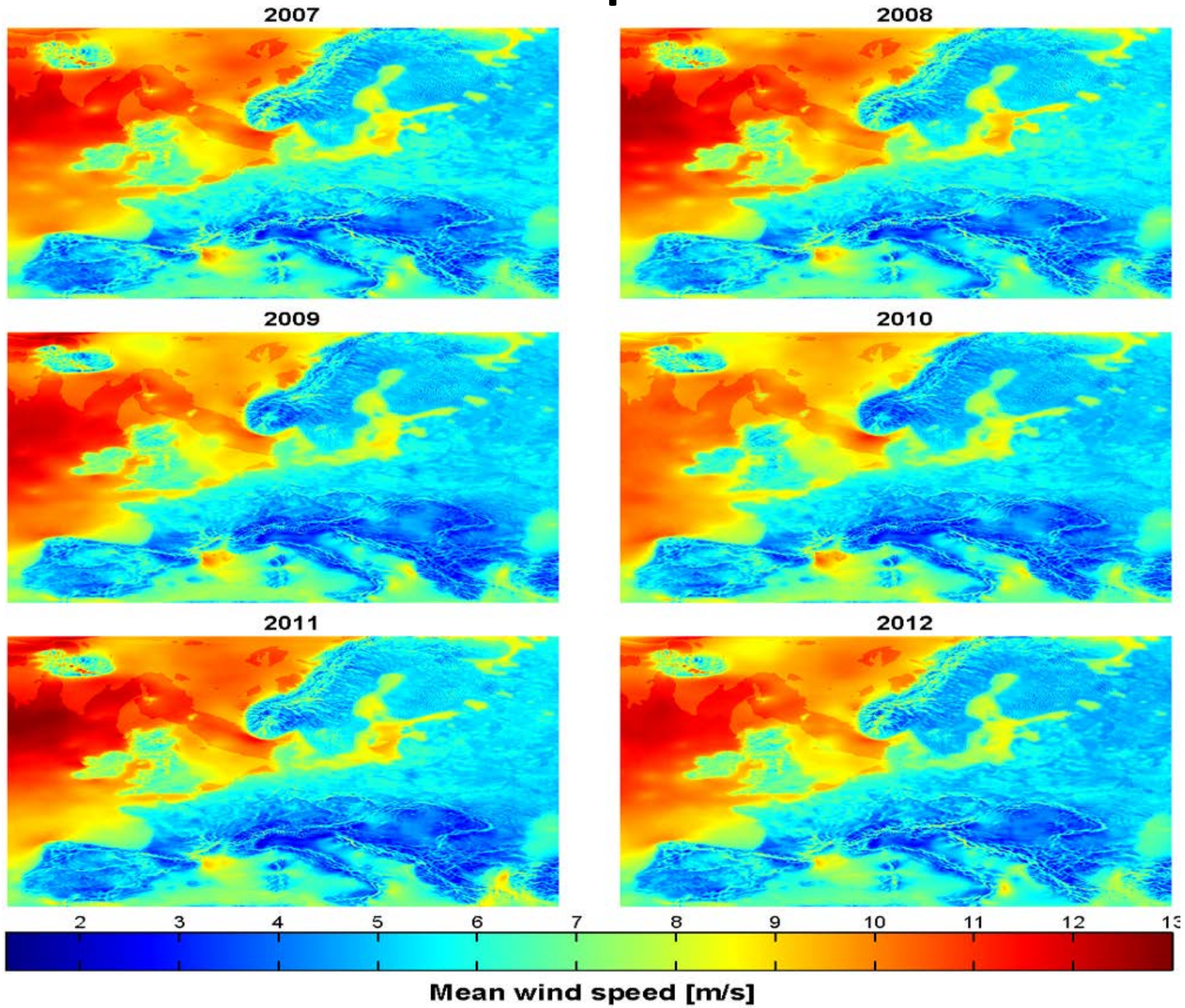
Renewable energy resources

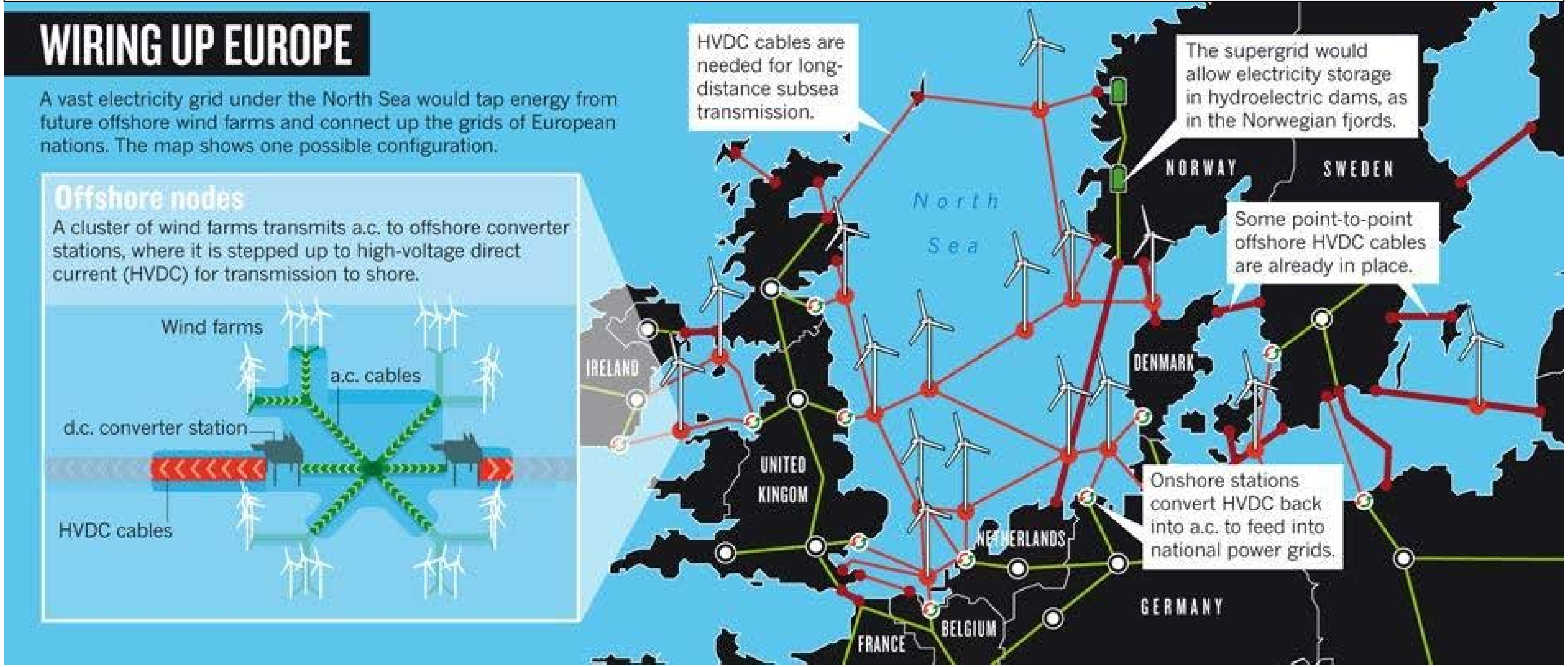


Ref: Tobias Aigner, PhD Thesis, NTNU

Wind Speeds



Increasing demand for spatial and temporal flexibility ➡ North Seas Offshore Grid (NSOG)

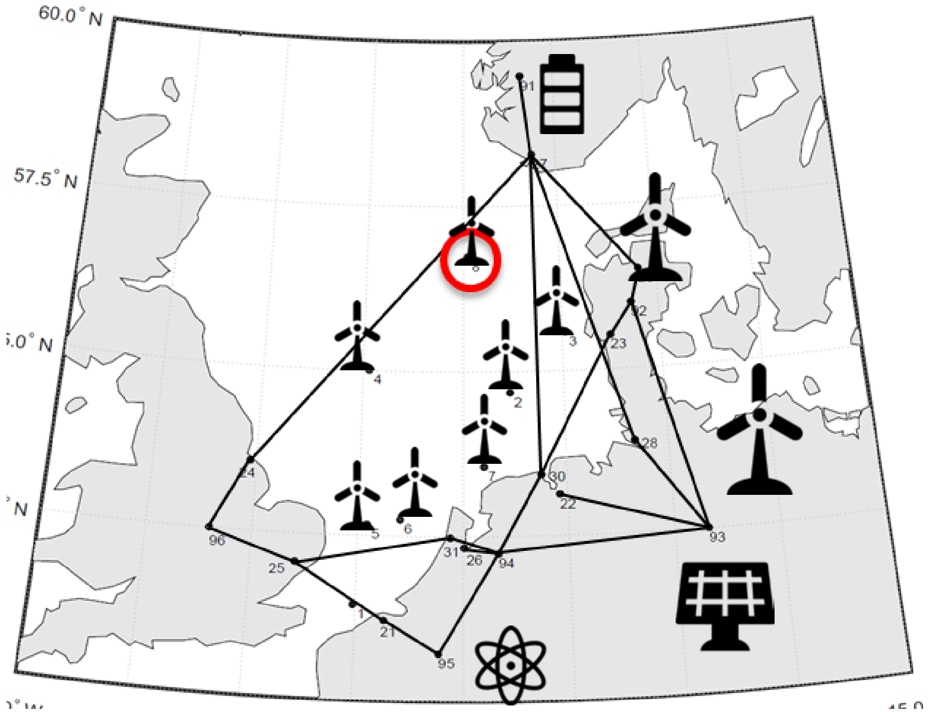


Ref: www.nature.com

The transmission expansion planning model

Offshore grid – context

- The main drivers are **large-scale integration of non-dispatchable** power generation and multi-national **trade**
- We want a tool to identify **good offshore grid layouts**
  - Useful for strategic planning (TSO's / governments)
  - Proactive in terms of offshore wind integration
- Important aspects
  - Optimal – minimize (socio-economic) costs
  - Robust – not overly sensitive to small changes in parameters
  - Uncertainty – underlying parameters might change
  - Energy policy – national effects in terms of generation portfolio
  - Climate policy – national effects in terms of emissions
  - Risk – investors risk attitude



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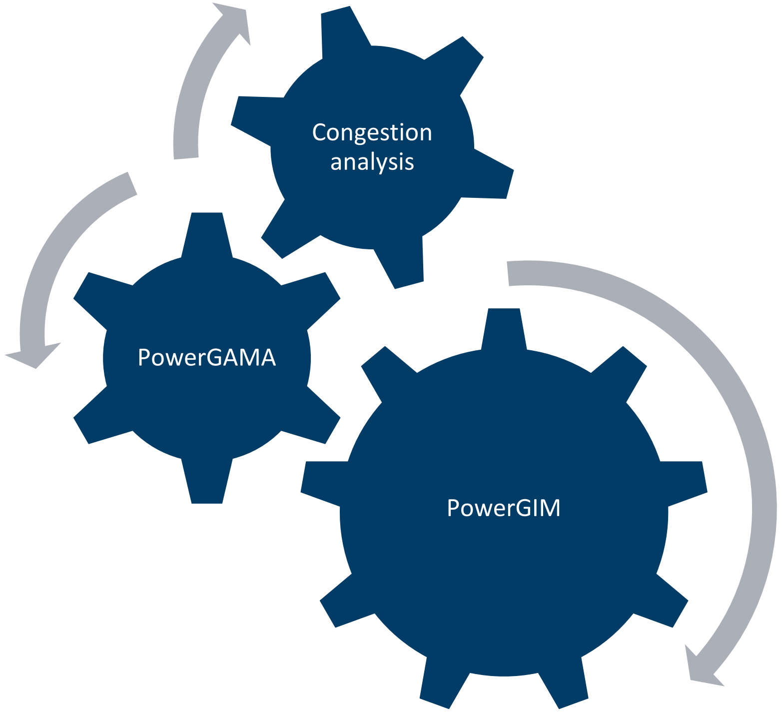
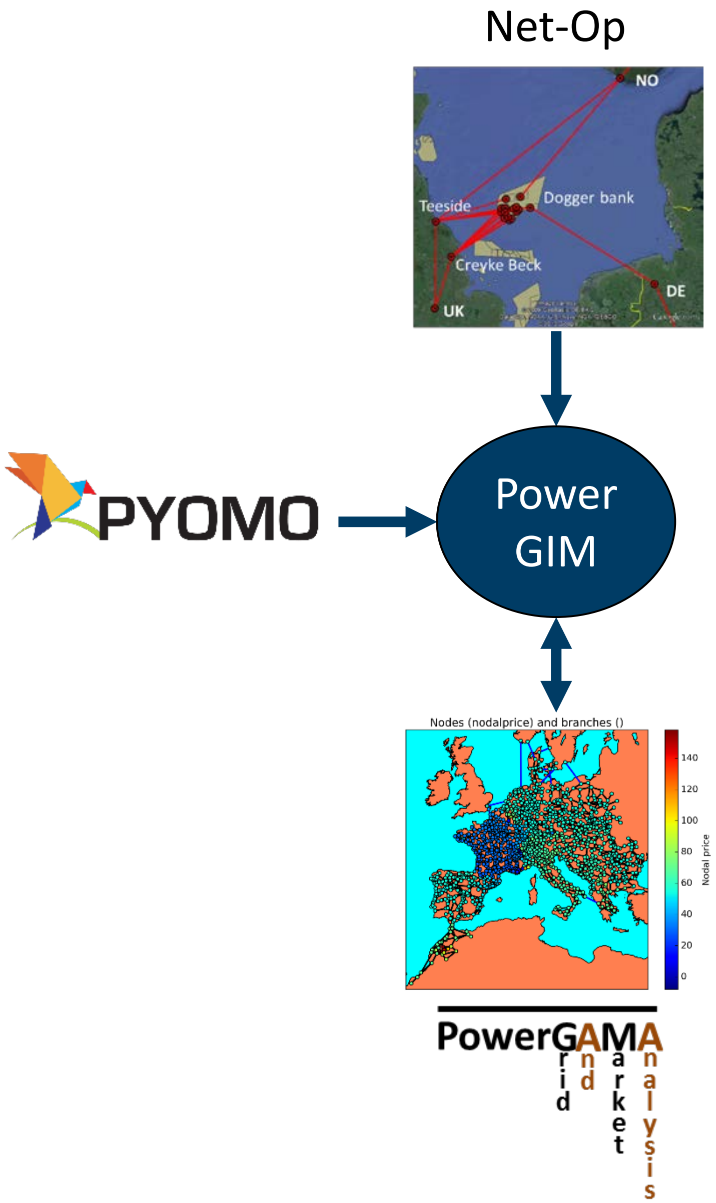
Our approach



- Linear optimisation
- Take into account:
  - Variability in renewable energy and prices/demand via time-series sampling
  - Different transmission technologies (cost categories)
  - NEW: Uncertain parameters via stochastic programming and scenarios
  - *future: Power flow constraints (not yet)*
- Considering:
  - Capacity investment costs in transmission (cables + power electronics + platforms)
  - Capacity investment costs in generation (per technology)
  - Market operation over sampled hours

PowerGIM

- PowerGIM = Power Grid Investment Module
  - A “proactive” expansion planning model
- Available as part of the open-source grid/market simulation package PowerGAMA
  - https://bitbucket.org/harald_g_svendsen/powergama
- Python-based, modelled with “Pyomo”
  - http://www.pyomo.org/
- Two-stage stochastic mixed-integer linear program (MILP)



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Model formulation

In words..	In maths..

In words..

- Minimize investment cost + operational costs

Subject to

- Market clearing
- Generation limits
- Curtailment
- Load shedding
- Branch flow limits (ATC // DC OPF // PTDFs)
- Capacity investment limits
- (Reserve requirements)
- (Renewable Portfolio Standards)
- (Emission contraints)

In maths..

$$
\begin{aligned}
\min_{x,y} \quad & FSC + a\frac{8760}{|T|}\sum_{s\in S}\pi_s SSC_s \\
\text{s.t.} \quad & FSC = \sum_{j\in B}(C_j^{fix}y_j + C_j^{var}x_j) + \sum_{n\in N} C^{node}y_n \\
& SSC_s = \sum_{i\in G}\sum_{t\in T} MC_i x_{its} + \sum_{n\in N}\sum_{t\in T} VOLL x_{nts} \\
& \sum_{i\in G_n} x_{its} + \sum_{j\in B_n^{in}} x_{jts}(1-l_j) - \sum_{j\in B_n^{out}} x_{jts} + x_{nts} = \sum_{l\in L_n} D_{lts} \quad \forall n\in N, t\in T, s\in S \\
& x_{nts} \le \sum_{l\in L_n} D_{lts} \quad \forall n\in N, t\in T, s\in S \\
& C_j^{fix} = B + B^d D_j + 2CL/CS \quad \forall j\in B \\
& C_j^{var} = B^{dp} D_j + 2CL^p/CS^p \quad \forall j\in B \\
& x_{its}^{cur} = P_{its}^{max} - x_{sit} \quad \forall i\in G, t\in T, s\in S \\
& P_{it}^{min} \le x_{its} \le P_{it}^{max} \quad \forall i\in G, t\in T, s\in S \\
& -(P_j^e + x_j) \le x_{jts} \le (P_j^e + x_j) \quad \forall j\in B, t\in T, s\in S \\
& x_j \le P_j^{n,max} y_j \quad \forall j\in B \\
& \sum_{j\in B_n} y_j \le M y_n \quad \forall n\in N \\
& x_j, x_{its}, x_{jts}, x_{nts} \ge 0, \quad y_j \in Z^+, \quad y_n \in \{0,1\}
\end{aligned}
$$

Expansion planning models

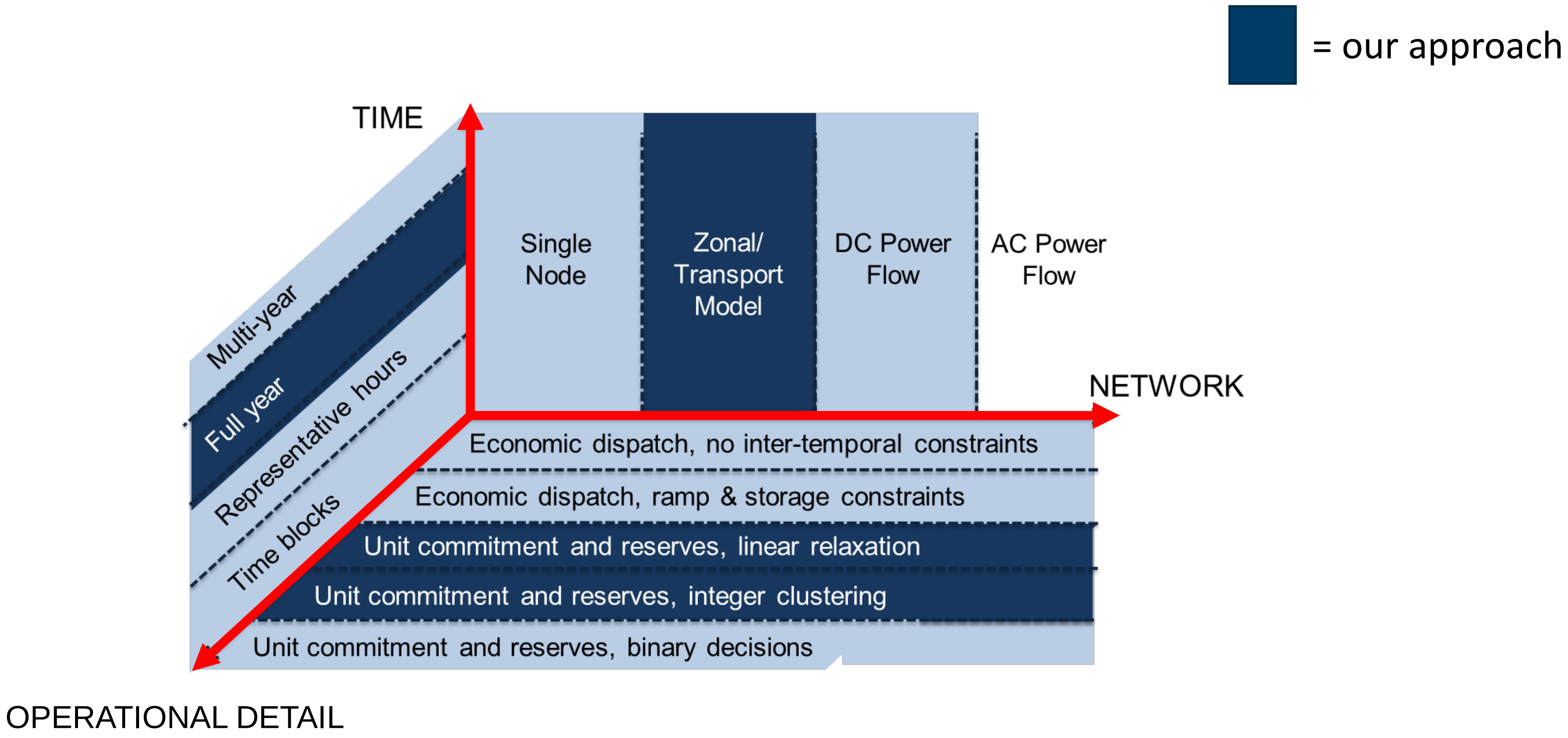
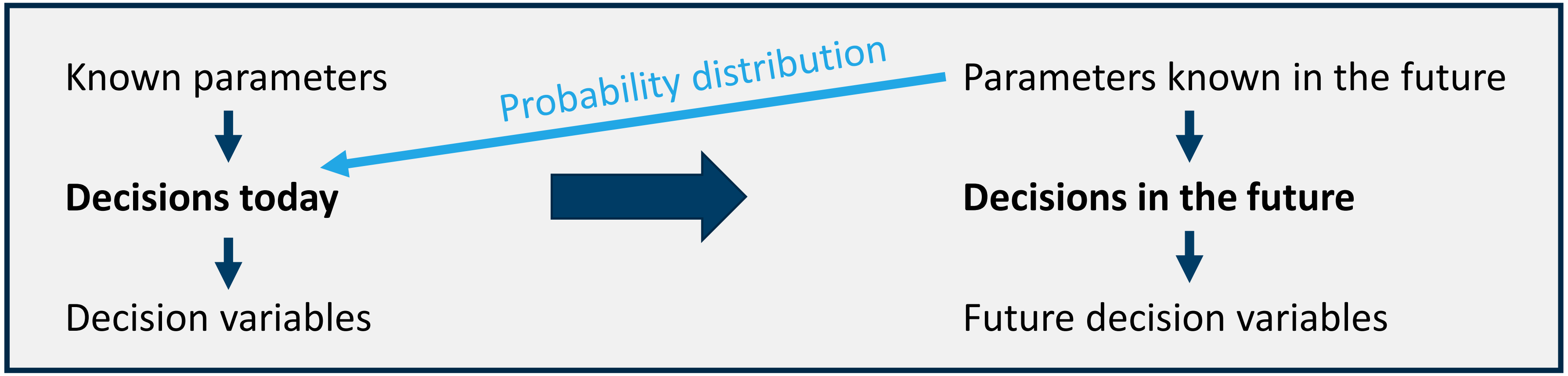


Figure: Jenkins, J., INFORMS, 2016.

Incorporating uncertainty

Two-stage optimization

- Basic idea:
  - When making decisions, some parameters are unknown. The best decision takes into account the probability distribution of those parameters
  - Use scenarios to represent probability distribution for uncertain parameters



Stochastic programming

- Two-stage problem:

$$\begin{aligned} \min_{x \in \mathbb{R}^n} \quad & g(x) = c^T x + E[Q(x, \xi)] \\ \text{subject to} \quad & Ax = b \\ & x \geq 0 \end{aligned}$$

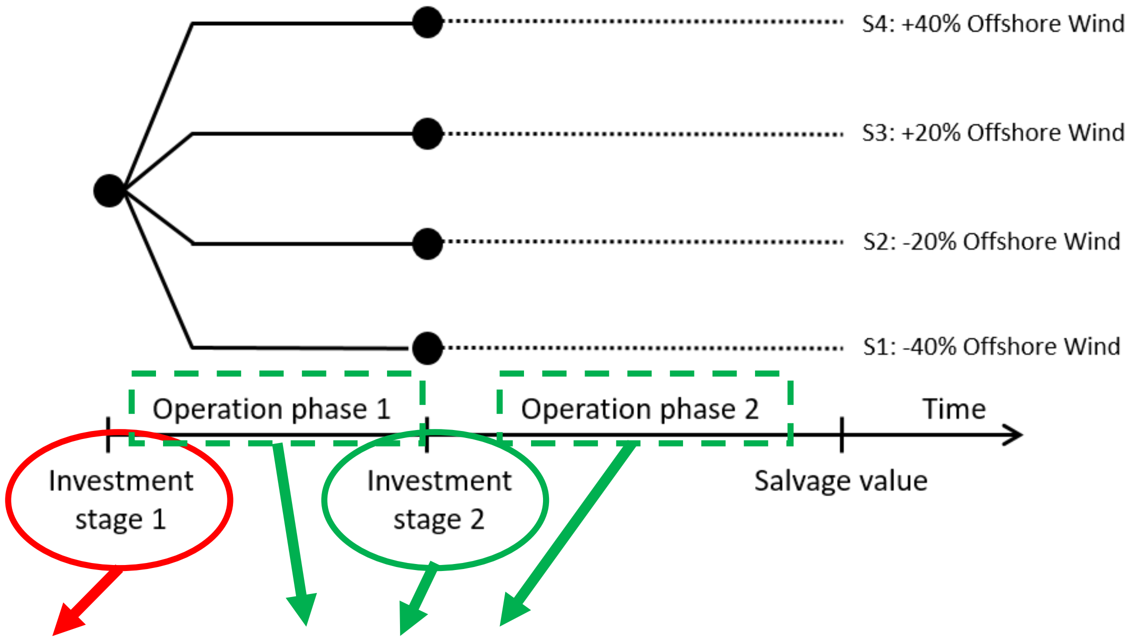
Expectation value of future (optimal) costs

  - x = first stage variables (to decide now)
  - ξ = uncertain data
  - Q is the optimal value of the second stage problem:

$$\begin{aligned} \min_{y \in \mathbb{R}^m} \quad & q(\xi)^T y \\ \text{subject to} \quad & T(\xi)x + W(\xi)y = h(\xi) \\ & y \geq 0 \end{aligned}$$

  - y = second stage variable (to be decided in the future)

Scenario tree



$$TC = \min_{x} c^T x + E_\xi[\min_{y(\omega)} q^T y(\omega)] \tag{1a}$$

s.t.

$$Ax \leq b \tag{1b}$$

$$T(\omega)x + Wy(\omega) \leq h(\omega), \quad \forall \omega \in \Omega \tag{1c}$$

$$x = (x_1, x_2) \geq 0, x_1 \in \mathbb{Z}^+, y(\omega) = (y_1(\omega), y_2(\omega), y_3(\omega)) \geq 0, y_1(\omega) \in \mathbb{Z}^+ \quad \forall \omega \in \Omega$$

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Solution method: progressive hedging

- Stochastic program formulation (deterministic equivalent):

$$\min_{x} \sum_{s \in S} p_s f_s(x_s)$$

$$x_s \in C_s$$

- Relax non-anticipativity to get scenario-s problem formulation:

$$\min_{x_s} f_s(x_s)$$

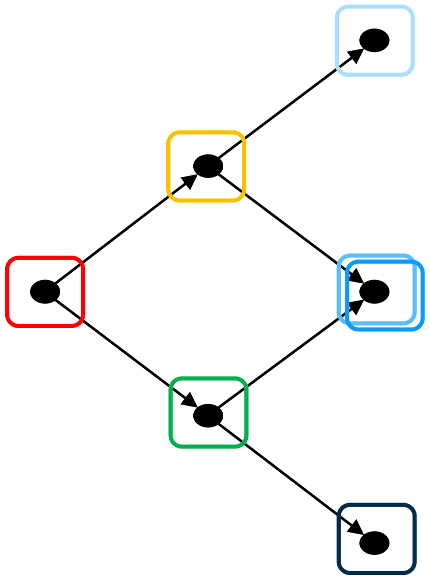
$$x_s \in C_s$$

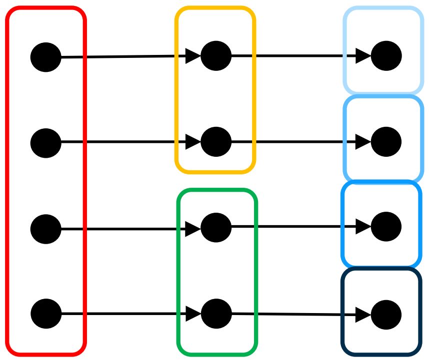
- Add penalty for non-anticipativity

If 1st stage variables are binary, this expression can be linearized

$$\min_{x_s} f_s(x_s) + \left[W^T x_s + \frac{\rho}{2}||x_s - \hat{x}||^2\right]$$

$$x_s \in C_s$$





Case study:
North Sea 2030 – Energy Revolution (Vision 4)

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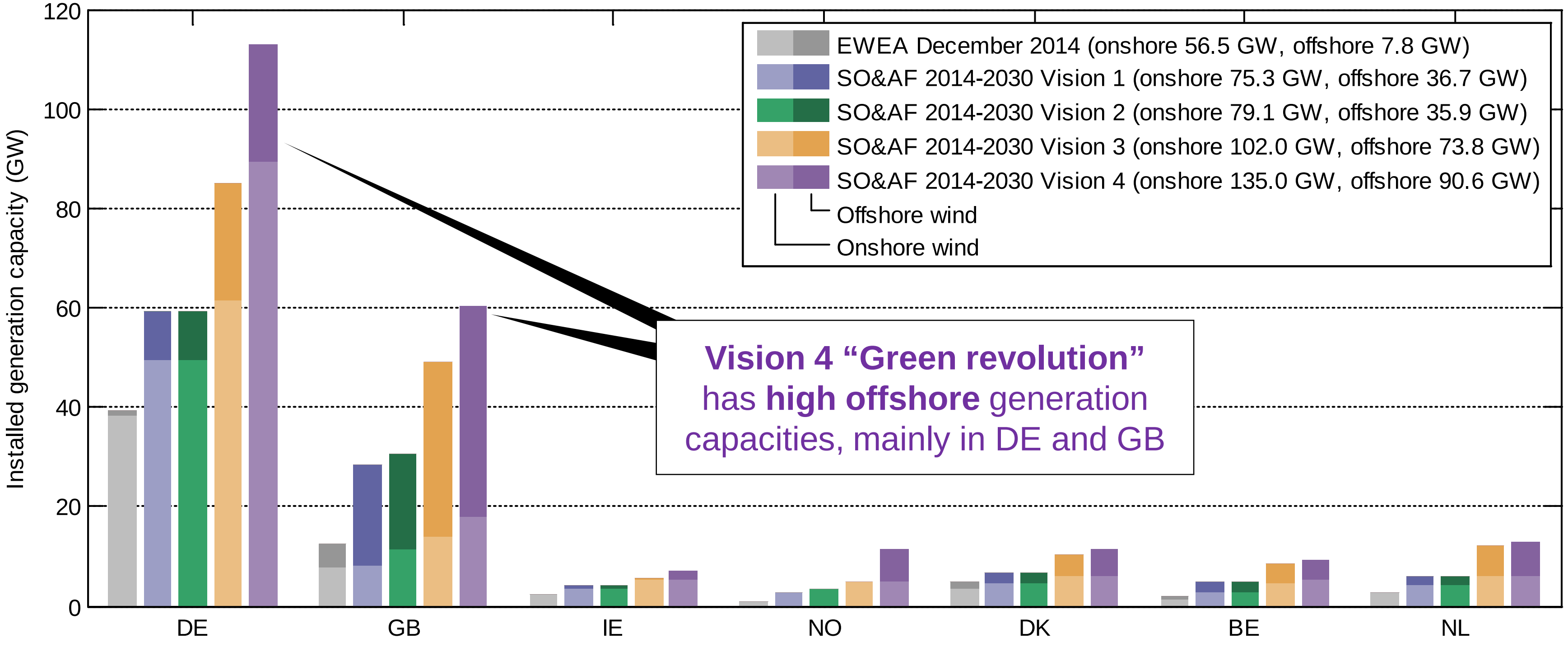
Base case scenario



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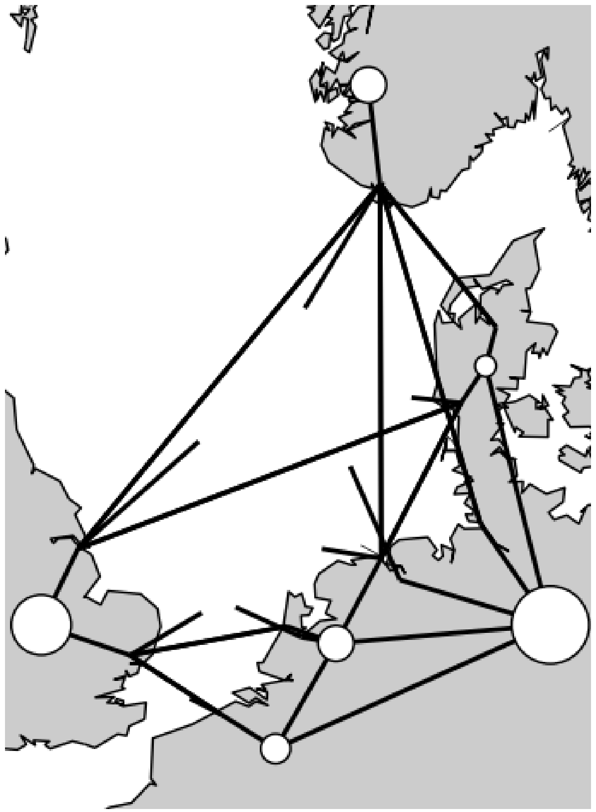
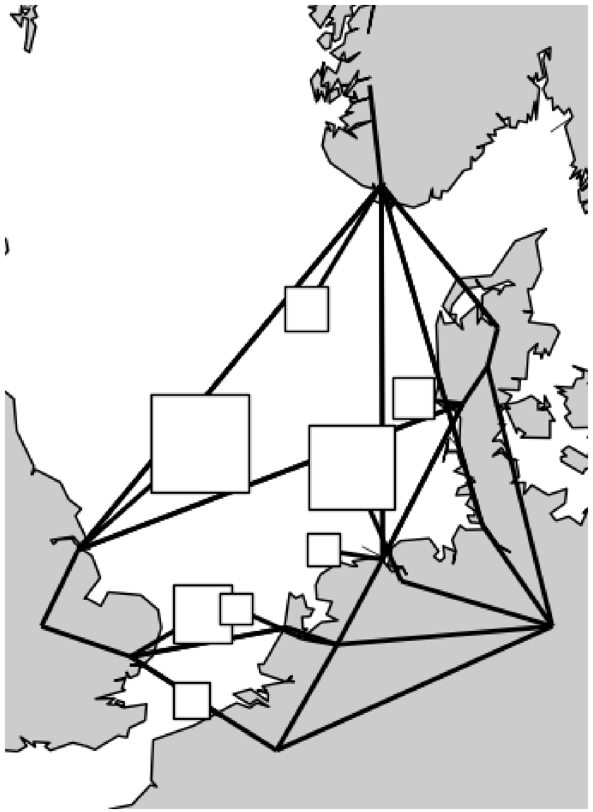
Base case scenario

Relative peak load

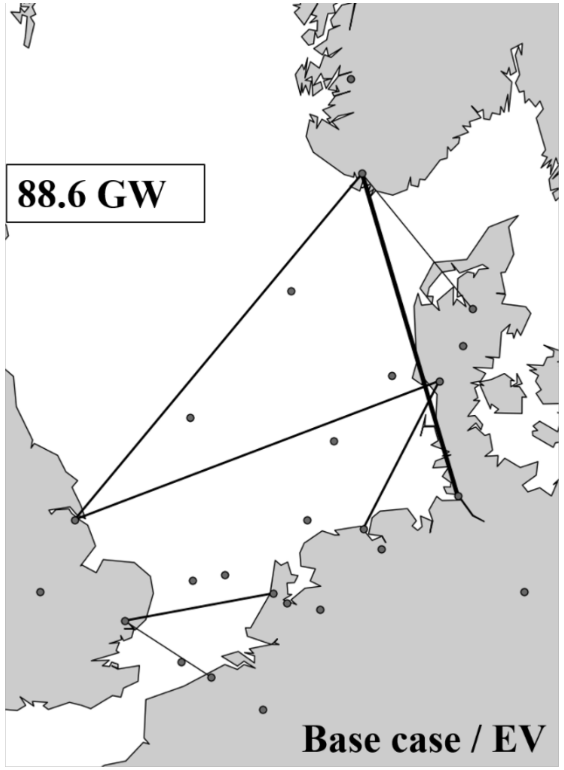


Relative offshore wind capacity



Deterministic: Expected value

No uncertainty taken into account

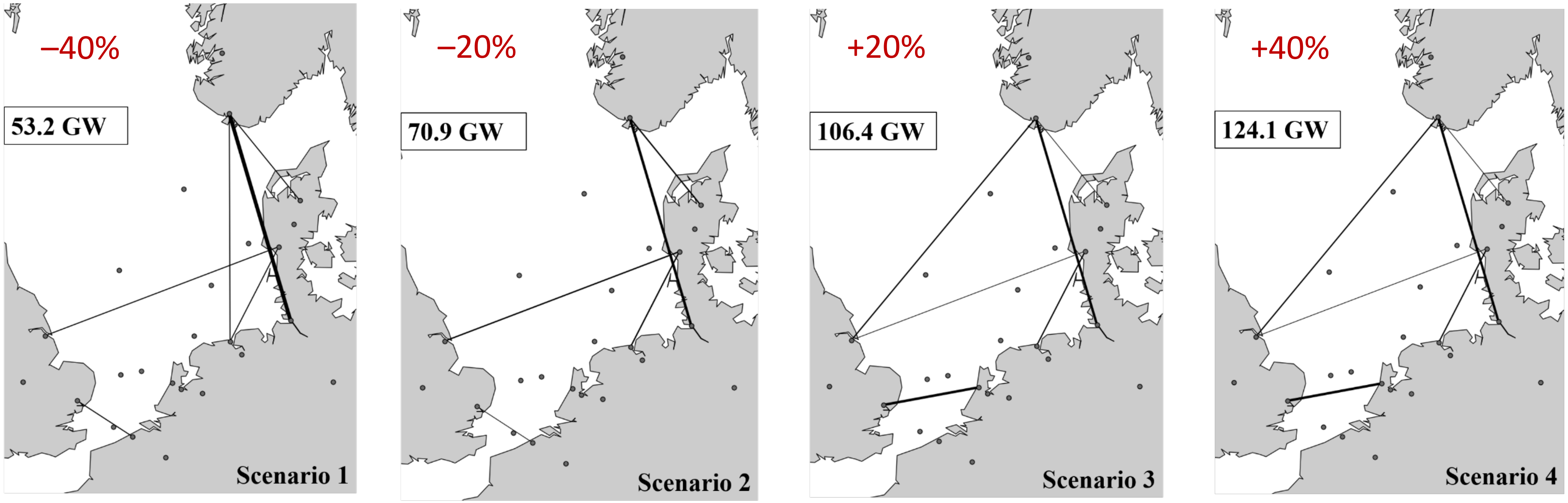


EV solution

Investment: 19.86 bn€
Total cost: 421.21 bn€

But actual operating conditions will not be as expected

Deterministic: Robustness analysis



	S1	S2	S3	S4	Expected value
EV solution	487.74	449.22	400.80	384.99	430.69
→ Investment costs	19.86	19.86	19.86	19.86	19.86
Deterministic solution	484.70	447.70	400.11	383.29	428.95
→ Investment costs	12.66	14.85	19.19	19.19	19.86
Value of information	3.04	1.53	0.68	1.70	1.74

With EV solution

With perfect foresight

Expected value of using the EV solution (EEV)

- The WS result might be difficult to interpretate since it contains a set of solutions (one per scenario)
- Tempting to use the EV scenario (only one solution)
- …but the resulting decision is still exposed to future scenarios
- -> EEV:

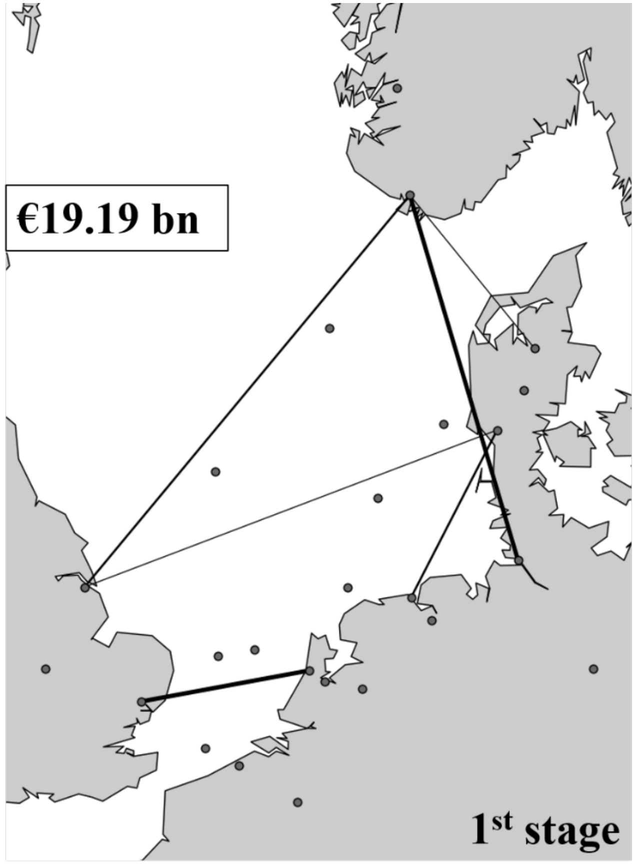
$$EV = \min_x \quad Z(x, \bar{\xi}) \text{ where } \bar{\xi} = E(\xi)$$

$$EEV = E_\xi[Z(\bar{x}(\bar{\xi}), \xi)]$$

€430.69 bn (EV €421.21 bn)

Stochastic: one investment stage

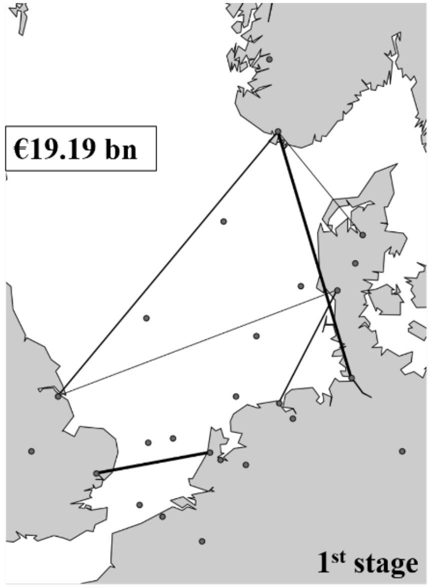
RP



- Uncertain offshore wind capacity taken into account
- No second stage compensating investments considered

Investment: 19.19 bn€
Total cost: 430.668 bn€

Stochastic: two investment stages



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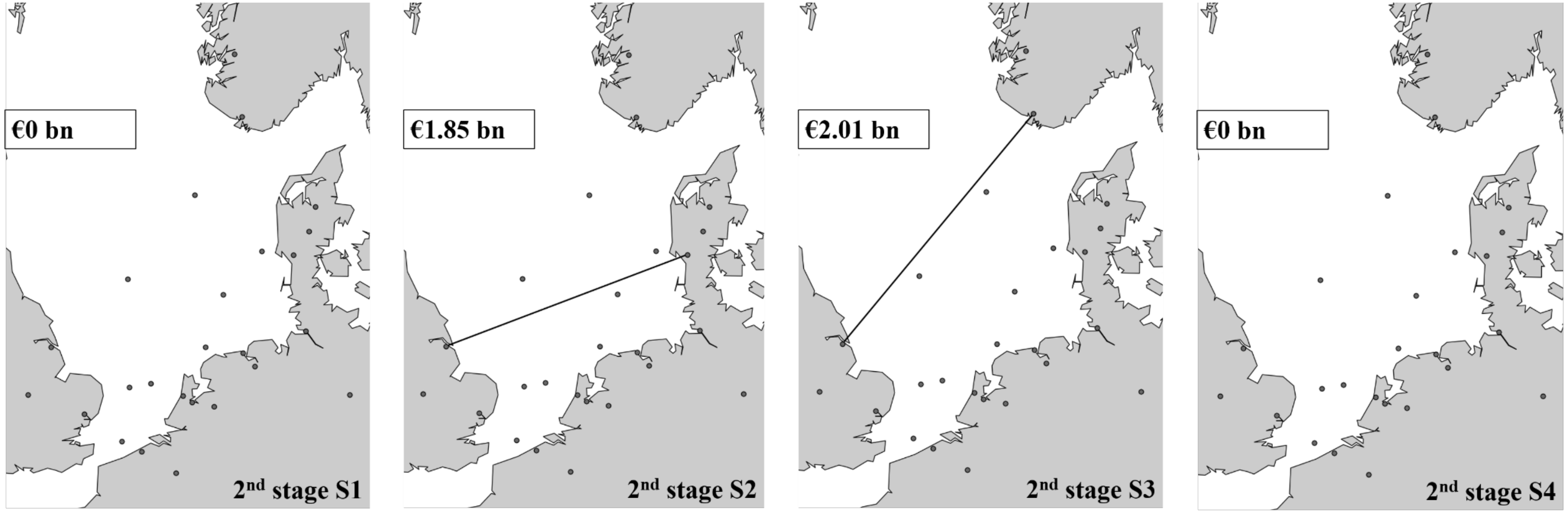

Stage 1 investment:
Almost the same as with only one investment stage

5 years later, when wind capacities are known

Expected total investment:
20.16 bn€

Expected value of perfect information (EVPI)

- The maximum amount that a system planner would be willing to pay for a "crystal ball"
- Benchmarks
  - Best available tool: a stochastic model (RP)
  - If she knew the future: deterministic solution of those scenarios (WS)
- The EVPI:

$$WS = E_\xi[\min_x Z(x,\xi)] = E_\xi[Z(\bar{x}(\xi),\xi)]$$

$$RP = \min_x \quad E_\xi Z(x,\xi)$$

$$EVPI = RP - WS$$

€1.74 bn (0.40% of RP)

Value of stochastic solution (VSS)

- Your best deterministic approach that accounts for some uncertainty: EEV
- Your best alternative that “properly” incorporates uncertainty: RP
- …which can be used to quantify the cost of ignoring uncertainty (equivalent to the VSS):

$$VSS = EEV - RP$$

€22.30 m (0.0052%)

Conclusions

- Deterministic solutions that copes with uncertainty might be hard to evaluate (many solutions) and/or give a cost-inefficient hedge against future scenarios
- Stochastic programs makes it possible to optimize one investment strategy that is cost-efficient against future scenarios (in contrast to EEV)
- Limitations of this study and related metrics (EVPI, EEV, VSS, and ROV)
  - The base case does already contain a strong grid infrastructure for 2030
  - Uncertainty is only represented through offshore wind capacity (wo/ exogenous curtailment cost)
  - A maximum amount of two investment stages limits the value of flexibility (ROV)
  - Last but not least; we use a model…
- "More is better" – eliminate risk and enhance flexibility

Real option value (ROV)

- The value of flexibility
- Flexibility is represented with two investment stages
- The system planner can postpone investments in order to learn about the offshore wind deployment

€22.41 m (0.0054%)

(Equivalent to financial options)