

Context

Techno-economic prospective studies for energy system planning involve:

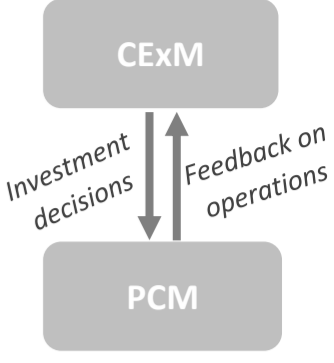
- Increasingly **complex models**, e.g. Capacity Expansion Models (CExM), Resource Adequacy Models (RAM), or Production Cost Models (PCM).
- But also **distributed tools, knowledge and data** among stakeholders,
- And (necessary) **structuring assumptions**: e.g. perfect foresight, perfect market, and exogenous (uncertain) parameters.



Literature

Several research works show promising results of **bi-directional linking strategies**, typically between CExM and PCM, by updating mathematical programming formulations through: parameters (choice of time slices [1], production/transmission capacities [2]); constraints (capacity credits of assets to satisfy the peak load [1], or estimated flexibility provision of assets over different time scales to satisfy a target [3]); or objective functions (e.g. generator revenue, or demand utility [4]).

Concurrently, **surrogate modelling**, especially through machine learning (ML), is drawing attention in energy system modelling [5-7], as for OPF problems [8-11], and more generally for optimisation [12].



Can model linking be efficiently combined with surrogate modelling to 1) reduce **computational burden**, 2) improve model **coverage and accuracy**, and 3) enable stakeholders to **share their models** while ensuring **data confidentiality**?

5 PhDs exploring linking and surrogate strategies:

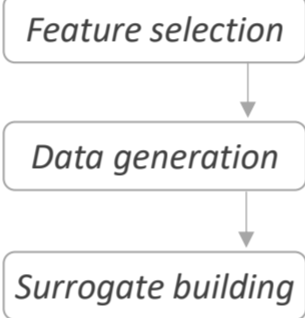
Surrogate modelling for bi-directional linking of sector-specific models

Exploring the combination of sensitivity analysis methods for **feature selection (Morris, Sobol, FAST)** with **surrogate modelling** methods (SVR, DNN, PINN, etc.), including hyperparameter tuning.

First toy problem:

PCM (Balmorel tool):
12 time steps, 6 nodes: DK, SE, NO, DE, NL, UK
Electricity & hydrogen

Next: Explore **transfer learning** for scaling, **GNN**, and integration with model coupling (with the Antares tool)



DTU
PhD: Tim Graulich; Supervisors: Marie Münster, Rasmus Bramstoft, Bissan Ghaddar

Multi-reduction surrogate methods for integrated sector modelling

Literature exploration phase for an **integrated framework**:

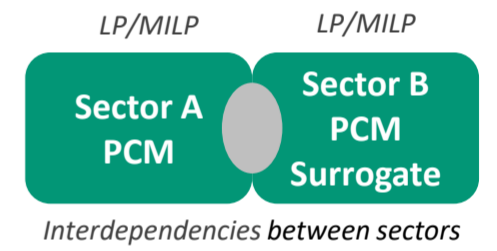
- Factor selection: knowledge based, sensitivity analysis based, ML based
- Surrogate modelling: reduction techniques (e.g. scenario, spatial aggregation), including ML based

Initial test case: Carriers: **Electricity & Gas** (hydrogen, methane)
Zones: **European core**

Next: Exploring **the impact of the model complexity** on factor selection. Exploring model integration and problem-solving strategies. Development of the integrated framework, with a focus on **result's interpretability**.



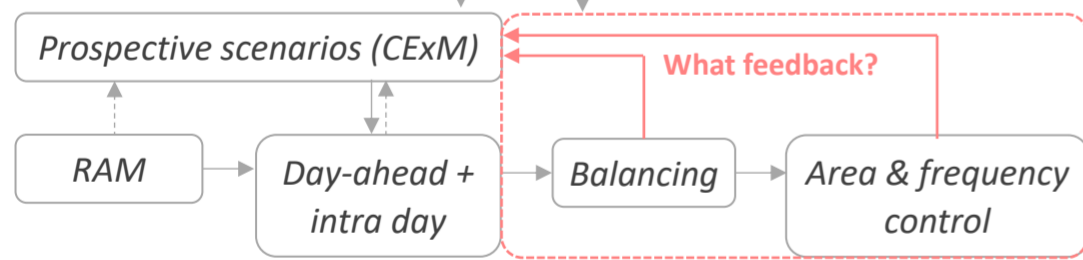
PhD: Emad Nematbakhsh; Supervisors: Luis Olmos, Sara Lumberras, Andrés Ramos



Bi-directional coupling of capacity expansion and balancing models

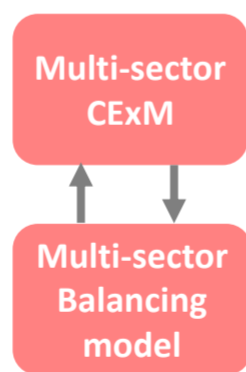
Literature exploration phase & use of the **Balancing Tool Chain** for assessing the **impact of VRE forecast errors**:

CorRES – VRE generation time series



Next: Define an initial feedback mechanism to enhance CExMs capabilities by incorporating VRE forecast uncertainties.

DTU
PhD: Mohammad Hassan Bahmani
Supervisors: Matti Koivisto, Kaushik Das



Statistical online surrogate building for energy systems assessment under uncertainty

Proposal for a modular, agnostic approach for accelerating energy system assessment and building surrogate models. Literature exploration phase:

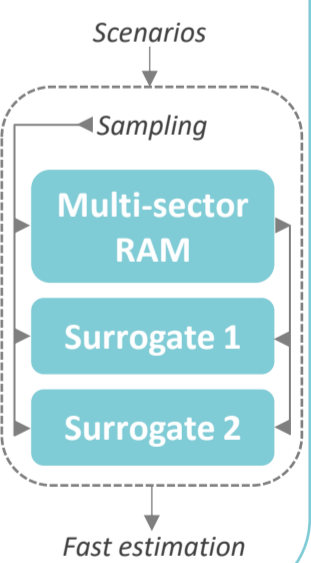
- The **Multi-Level-Monte Carlo** method [13], with surrogate model(s) (e.g. Gaussian process, CNN, DNN, SVR),
- built from an **online learning** strategy locating the most informative region (e.g. based on active learning, importance / uncertainty sampling, query by committee).

Applications: RAM, CExM (e.g. for accelerating Bender's decomposition approaches), evaluation of capacity values, generating alternatives etc.

Next: First implementation of the framework on toy problems and testing of multiple surrogate and learning strategies.



PhD: Ruiqi Zhang; Supervisors: Simon Tindemans, Miloš Cvetković

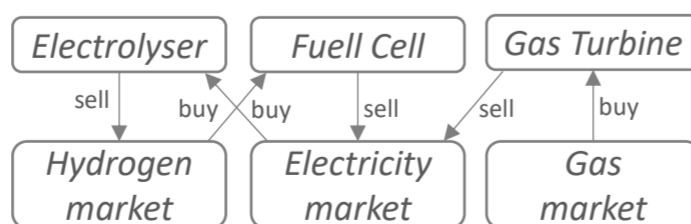


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Unperfect market surrogate models for energy system modelling

Evaluate the validity of the **perfect market assumption** in PCMs. Proposal for a **multi-leader, multi-follower Stackelberg game** architecture formulated into an EPEC to capture market inefficiencies:



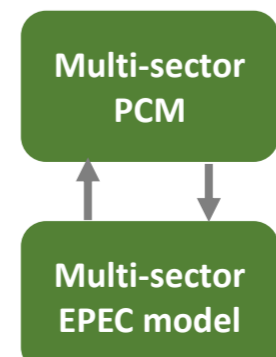
Usual solving process: Gauss-Sneidel Algorithm (iterative solving of individual MPEC, high computation burden)

Approximate the EPEC with a surrogate model? (Dynamical System, CNNs, Transformers, Deep Belief Networks or Behavioural Networks?)

Next: Couple the EPEC model with usual PCMs.



PhD: Jan Ot Piña Urgell; Supervisors: Miloš Cvetković, Simon Tindemans



Acronyms

- CExM: Capacity Expansion Models
- CNN: Convolutional Neural Network
- DNN: Dense Neural Network
- EPEC: Equilibrium Problem with Equilibrium Constraints
- ERAA: European Resource Adequacy Assessment
- FAST: Fourier Amplitude Sensitivity Test
- ML: Machine Learning
- MPEC: Mathematical Problem with Equilibrium Constraints
- PCM: Production Cost Models
- PINN: Physics-Informed Neural Network
- RAM: Resource Adequacy Models
- SVR: Support Vector Regression
- TYNDP: Ten Year Network Development Plan

Project manager: Etienne Cuisinier (etienne.cuisinier@cresym.eu)

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