Using Multi-Physics Simulation to Estimate Energy Flexibility for Local Demand Response Strategies in a Microgrid

Iker Landa del Barrio

Presented by: Luigi Vanfretti

Advisors:
Marco Quartulli (Vicomtech)
Julen Cestero (Vicomtech)
Naiara Aginako (UPV/EHU)

Content of the presentation

- Description of the Scenario
- Solution Implementation
- Results

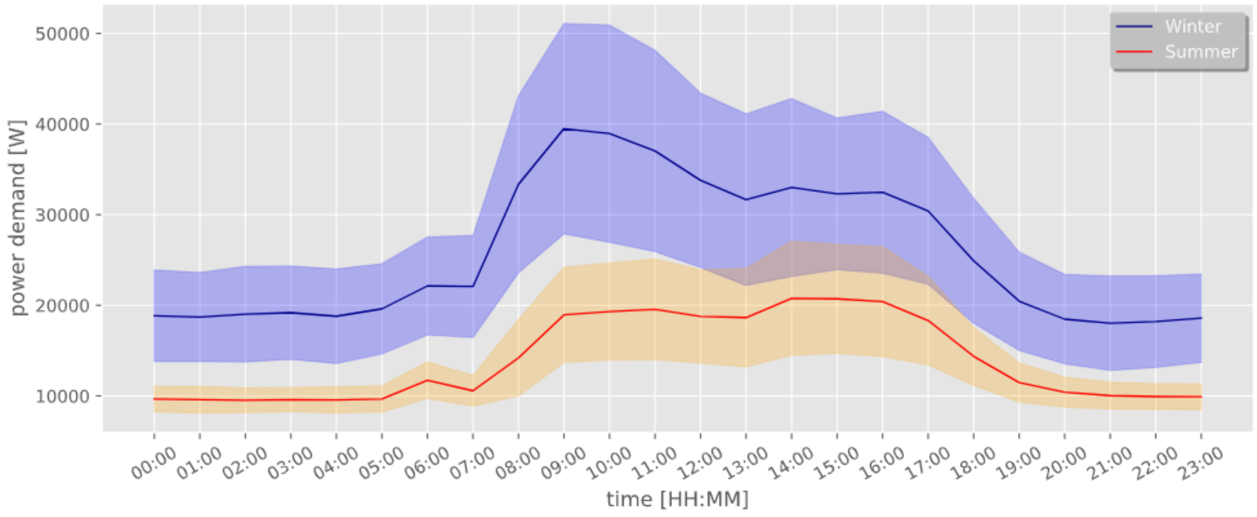
DESCRIPTION OF THE SCENARIO

Description of the Scenario

- ESTIA university campus in South-West France

- The work presented here addresses the synthetic data generation of certain loads to support DR strategies design and validation

Description of the Scenario



- University campus with collective self-consumption between different buildings and local PV generation
- A local Demand Response (DR) program using MPC is proposed for a optimised use of the local generation
- The estimation of the demand is a crucial input for the proposed DR program
- Limited access to historical data (2 months of PV generation and 1 year of general demand). Also
- Unavailable disaggregated demand data from certain loads

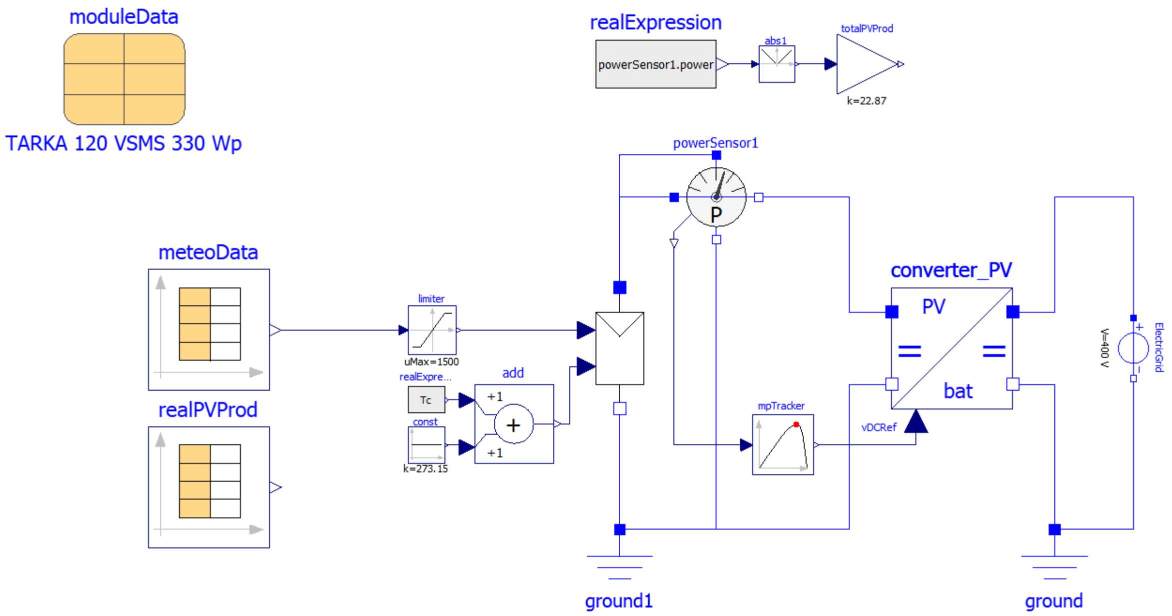
Description of the Scenario

Load Type	Power [kW]	ToU [h]
HVAC	15	Variable
Electric Car BT Charger	11	3
Water Heating System	1.2	Variable

- Selected loads for DR actions:
  - Electric Car Battery Charger
  - Air Heating System (HVAC)
  - Water Heating System
- The charger's demand is assumed to be constant when activated
- The demand of the heating systems cannot be assumed as constant, so a dynamic estimation is made

SOLUTION IMPLEMENTATION

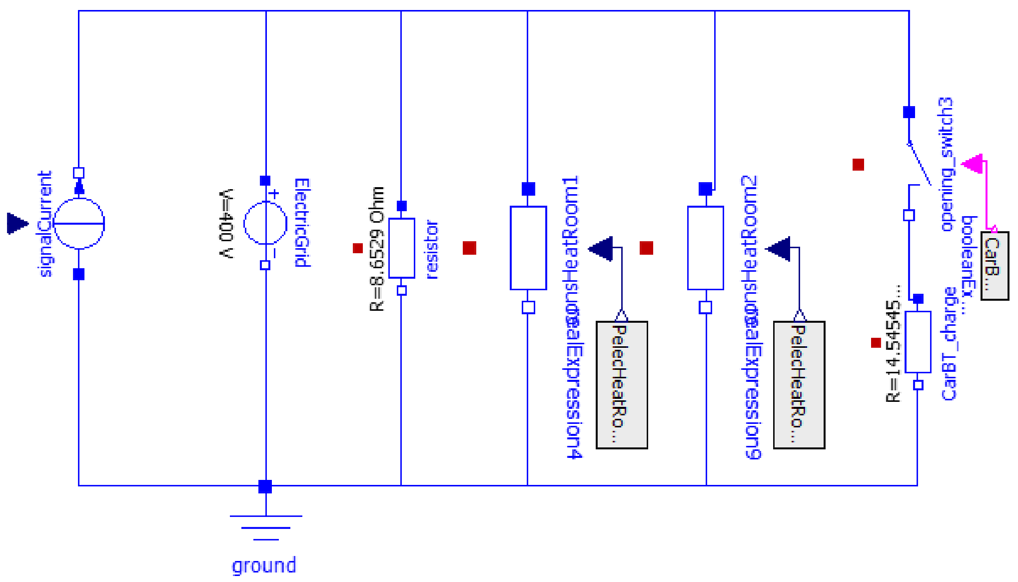
Solution implementation – Maximal PV generation estimation



$$T_c = T_{air} + \frac{G}{G_{NOCT}} \cdot \frac{9.5}{5.7 + 3.8 \cdot V_{wind}} \cdot \frac{T_{c_{NOCT}}}{T_{a_{NOCT}}} \cdot \left(1 - \frac{\eta_c}{\tau\alpha}\right)$$

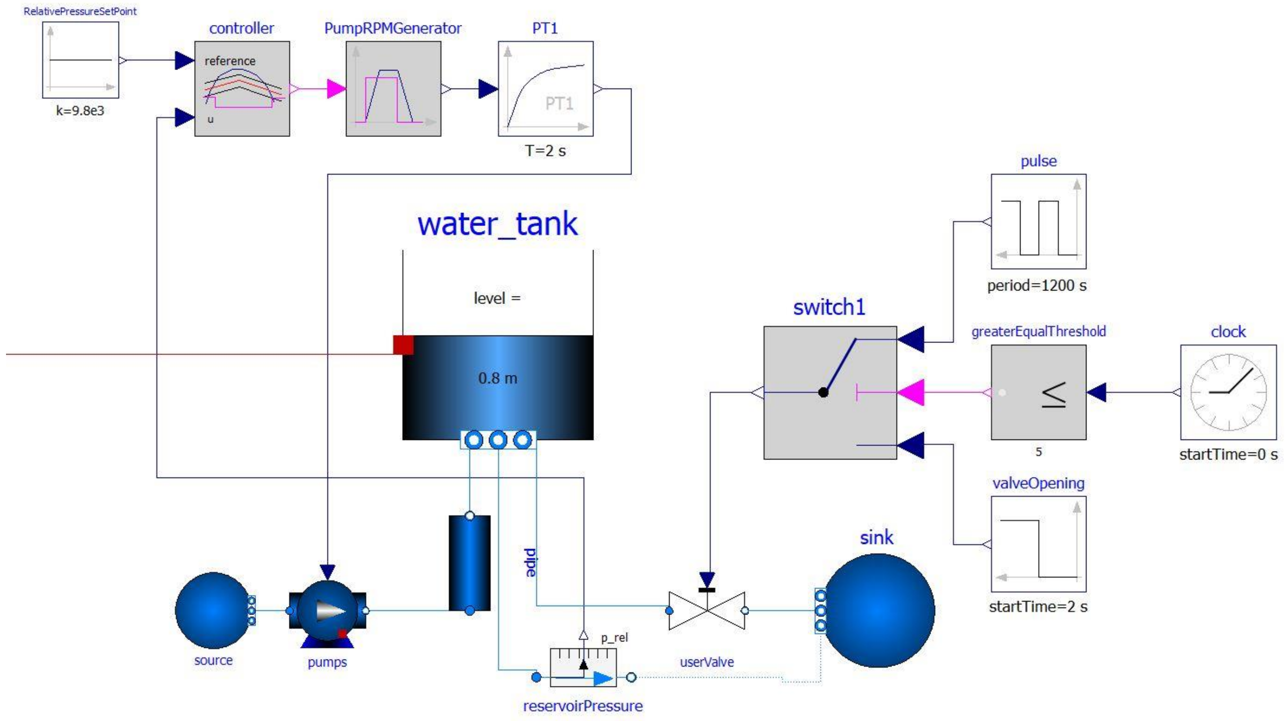
- The converter output is set to the campus' simulated microgrid operating voltage (400 VDC)
- A maximal production estimation is made neglecting losses due to orientation, shades, conversion, and conduction
- The PV cells surface temperature is estimated computing meteo data
- The PV generation estimator uses both *PVSystems* and *Photovoltaics* libraries

Solution implementation – Electric section



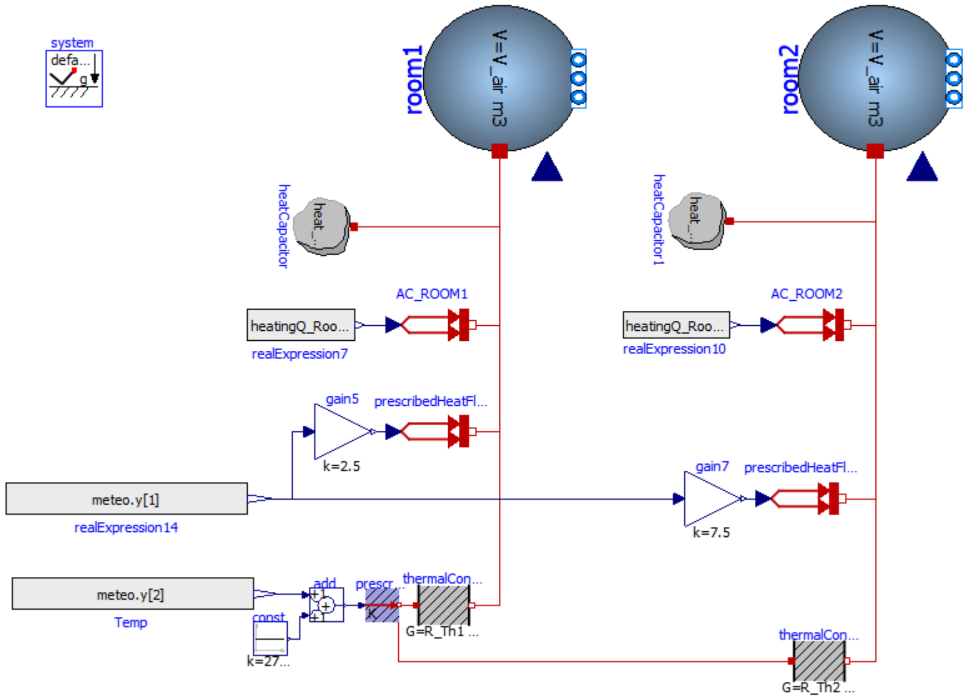
- Continuous voltage/current for computational costs matters
- PV generation is inserted using a .txt file and emulated with a signal current block
- Connection point with the general grid
- Loads are activated using ideal switches

Solution implementation – Water heater environment



- Water consumption simulated using a user valve and assuming consumption from the users by a *pulse generator*
- Refill control through an hysteresis controller

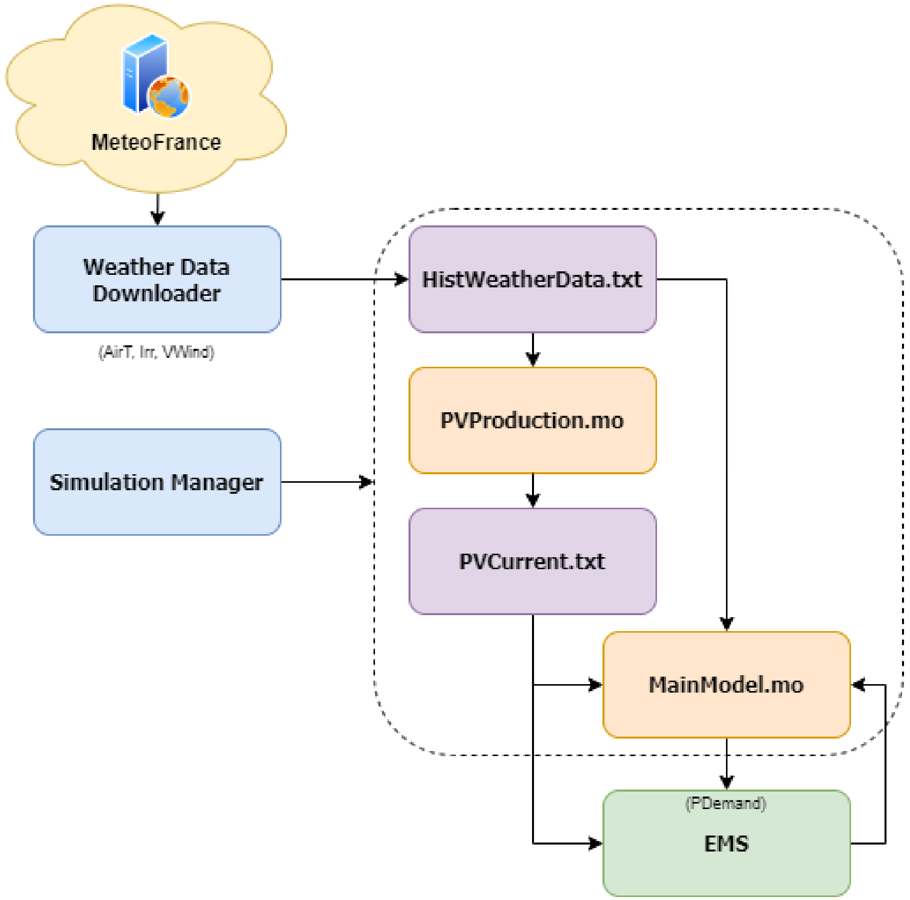
Solution implementation – HVAC environment



- Thermal resistor and capacitor are used to represent the envelope and thermal inertia of the building

- Thermal contribution and COP of the HVAC system is calculated dynamically depending on the external temperature

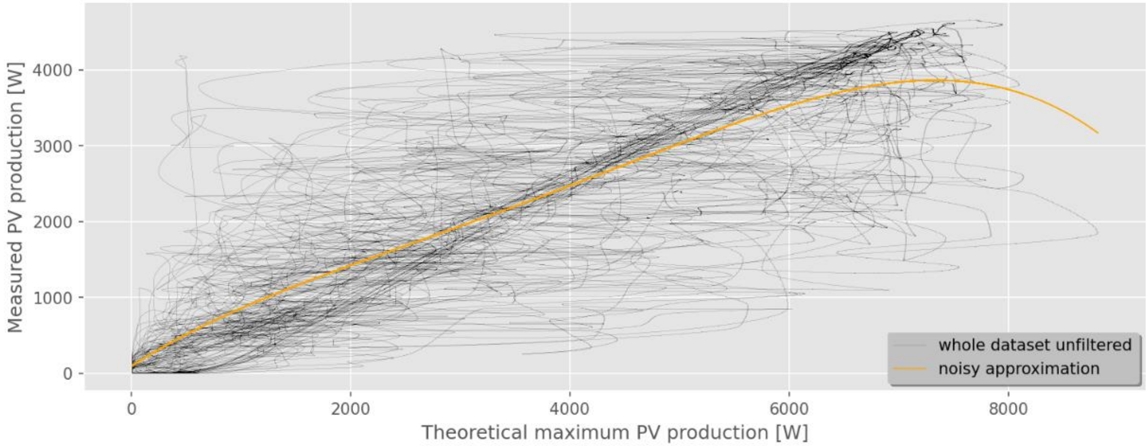
Solution implementation – Environment programming interface

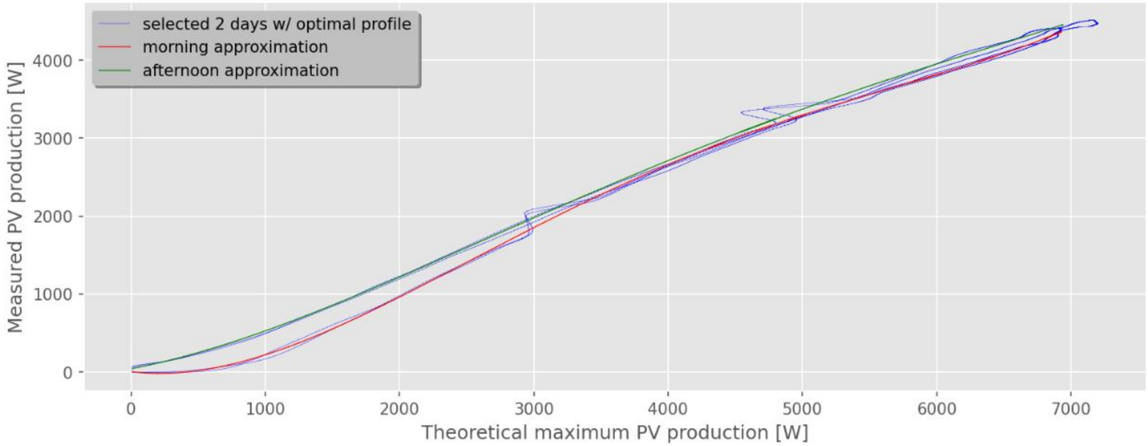


- Use of OMPython to connect OM with external algoritmia for simulation execution and data analysis
- Weather data is downloaded online using a MeteoFrance subscription
- Data is communicated between models using txt files

RESULTS

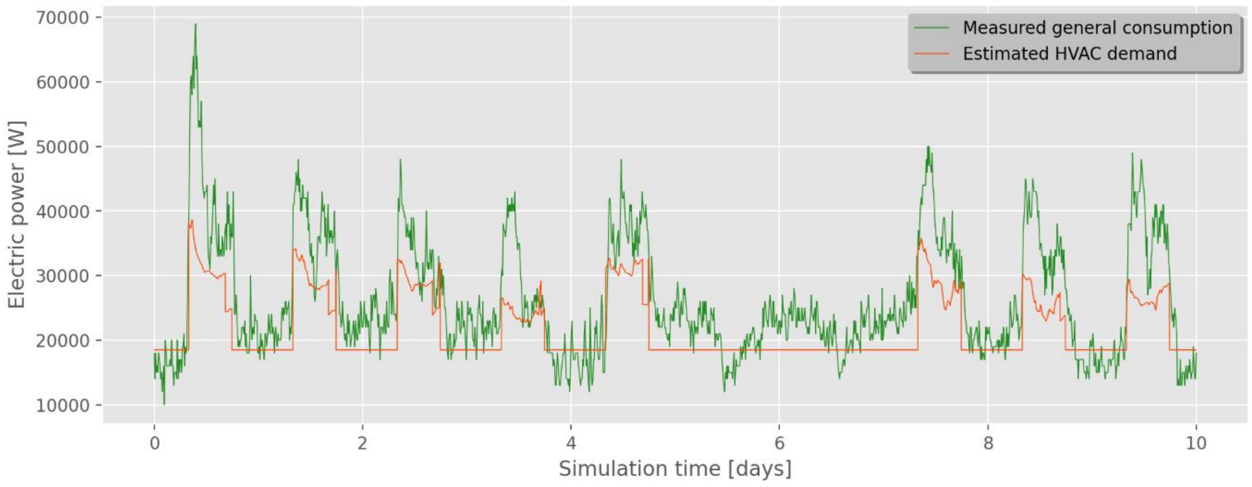
Results – PV prod. estimation results and approximation





- PV generation estimation is validated with nearest available meteo data source
- Estimation produces fast-shifting results due to sudden changes in meteo data
- Filtering is implemented selecting 2 days with optimal profiles
- Power losses are accounted in the prediction through a polynomial approximation

Results – HVAC demand estimation



- HVAC demand estimation is compared with general measured demand in a 10 days experiment
- The estimation results show correspondence to the main changes in the measured general demand
- Correlation between both variables is $\rho_{\mathbf{Sim,Real}} = \mathbf{0.852}$

THANKS FOR YOUR ATTENTION

TIME FOR QUESTIONS