Technoeconomics of Energy Systems laboratory - TEESlab

TEESlab **M**odeling suite – **TEEM**: High-resolution energy system simulation & optimization models

Introduction

TEEM, the **TEE**Slab **M**odeling suite, is an ensemble of high-resolution energy system simulation and optimization models, which comprises of three main models:

1. the **B**usiness **S**trategy **A**ssessment **M**odel (BSAM),
2. the **A**gent-based **T**echnology ad**O**ption **M**odel (ATOM), and
3. the **D**ynamic high-**R**esolution d**E**mand-sid**E** **M**anagement (DREEM) model.

BSAM is an agent-based electricity wholesale market simulation model which simulates the complex operations within a power pool central dispatch Day Ahead Market. The model simulates electricity generators as entities who progressively learn to bid their capacities in a day-ahead competitive wholesale market, with ultimate goal the maximization of their profits. In parallel, a unit commitment and optimal dispatch algorithm calculates the quantities injected by each generation unit, the system marginal price, the system costs, as well as, derived outputs such as CO_2 emissions and profits of each generator. The model can support cost-benefit analysis of future policy and/or technology deployment scenarios. It is very flexible since it simulates the power generators as agents that compete with each other and adapt to policy and/or market changes.

ATOM simulates the dynamics of technology adoption among consumers. The model is supported by a complete framework for parameter estimation based on historical data, and for the quantification of the uncertainty that governs its ability to replicate reality.

DREEM is a fully integrated dynamic high-resolution model resolving key features that are not found together in existing Demand-Side Management (DSM) models. The model serves as an entry point in DSM modeling in the building sector, by expanding the computational capabilities of existing Building Energy System (BES) models to assess the benefits and limitations of demand-flexibility, primarily for consumers, and for other power actors involved.

and two model plugin toolboxes:

The **A**daptive Policymak**I**ng **M**odel (**AIM**) provides real time visualizations of adaptive policy maps, showing alternative pathways leading to desired policy outcomes. The interactive policy maps facilitate interactive stakeholder consultation for the design of policies which commit to short term objectives and define future contingency actions to prevent policy failure in case of unexpected contextual parameter changes.

The **ST**atistical approximation-based mod**E**l **EM**ulator (**STEEM**) addresses computational burdens that are typically raised by simulation models' computational complexity, resulting in time-consuming simulations. Using machine learning techniques, STEEM is trained using inputs and outputs from original models, and then is used to make quick approximations of outputs given new inputs.

TEEM suite

BSAM Business Strategy Assessment Model

is a wholesale market simulation framework which consists of two modules: **(i)** a unit commitments and optimal dispatch module that calculates the cost-optimal dispatch of electricity generation units, and **(ii)** an agent-based module that simulates the bidding behavior of electricity generators (agents) who progressively learn to bid their capacities in a day ahead competitive wholesale market, with ultimate goal the maximization of their profits. The model can support cost-benefit analysis of future policy and/or technology deployment scenarios, to quantify the effects of different policy measures and market developments on the electricity price and the fuel mix. The initial modeling framework is presented by Papadelis et al., (2012) [1], while it was further developed during the H2020 project “TRANSrisk”, where it was calibrated for the case of the Netherlands, to evaluate the impacts, costs, and benefits of increasing the renewable energy system share (specifically solar PV) in the electricity mix, while reducing the share of fossil (i.e. coal and gas) and nuclear generators. The model has been also used to measure the impact of an energy storage-based transition on electricity prices, for different levels of installed PV capacity and market share of storage in the Greek power sector. More information is presented by Nikas et. al (2018) [2].

Requirements

Inputs	Outputs
Hourly demand projections, Generator-specific data (fuel type, technology, nominal power, technical minimum power, efficiency, minimum uptimes and downtimes, availability, cost per production unit, costs of ‘hot’/’cold’ start-up, must-run market rule, percentage of biomass co-firing for coal generators) Projections of electricity generation from wind and solar sources, Projections of electricity available from water sources, separately for each drainage basin and on a monthly resolution, Fuel price projections (coal, oil, natural gas, biomass, etc.), Import prices projection, Wind and solar subsidy policies, Market-specific rules and regulations, such as max allowed electricity price, required primary reserve, remuneration methods for RES, etc, **Input data in CSV format**	For each electricity producer: power produced, cost and profit, System Marginal Price (SMP), System electricity generation costs, The optimal electricity mix in order to economically match the demand over the modelled period, CO_2 emissions **Output data in CSV format**
Language: Python source code	

ATOM Agent-based Technology Adoption Model

is an agent-based model that simulates the dynamics of technology adoption among consumers. The model was developed during the H2020 project “TRANSrisk” and has already been used to provide scenarios of new capacity additions for small-scale PV (i.e. 1kW-10kW), in Greece, under the Net-Metering scheme, currently in effect and a proposed Self-Consumption scheme, that subsidizes residential electricity storage (similar to the respective support scheme in Germany). Supported by a complete framework for parameter estimation based on historical data, ATOM can be used to quantify the behavioural uncertainty that governs the technology adoption scenarios derived. More information is presented by Stavrakas, Papadelis and Flamos (2019) [3].

Requirements

Inputs	Outputs
Historical data of demand for small-scale PV investments, PV costs, Battery costs, Retail price, Compensation schemes for consumers, **Input data in CSV format**	Scenarios of new PV capacity addition **Output data in CSV format**
Language: Python source code	

DREEM is a fully integrated dynamic high-resolution model resolving key features that are not found together in existing Demand-Side Management (DSM) models. The model serves as an entry point in DSM modeling in the building sector, by expanding the computational capabilities of existing BES models to assess the benefits and limitations of demand-flexibility, primarily for consumers, and for other power actors involved. The model was developed during the H2020 project “TRANSrisk”, and its novelty lies mainly in its modularity, as its structure is decomposed into individual modules characterized by the main principles of component- and modular-based system modeling approach, namely “the interdependence of decisions within modules; the independence of decisions between modules; and the hierarchical dependence of modules on components embodying standards and design rules.”

This approach allows for more flexibility in terms of possible system configurations and computational efficiency towards a wide range of scenarios studying different aspects of end-use. It also provides the ability to incorporate future technological breakthroughs in a detailed manner, such as the inclusion of heat pumps or electric vehicles, in view of energy transitions envisioning the full electrification of the heating and transport sectors. The latter makes the DREEM model competitive compared to other models in the field, since scientific literature acknowledges that there are limitations to how much technological detail can be incorporated without running into computational and other difficulties. The model also supports the capability of producing output for a group of buildings and can also serves as a basis for modelling domestic energy demand within the broader field of urban energy systems analysis. The model can be coupled with BSAM to support the evaluation of the expected impacts from bringing demand-flexibility into the power market, and/or with ATOM to simulate the adoption of technologies that can be regarded as flexibility enablers (i.e. small-scale PV, battery storage, smart thermostats, etc.). More information is presented by Stavrakas and Flamos (2020) [4].

The architecture of the model, as it currently stands, is visualized in **Figure 1** below.

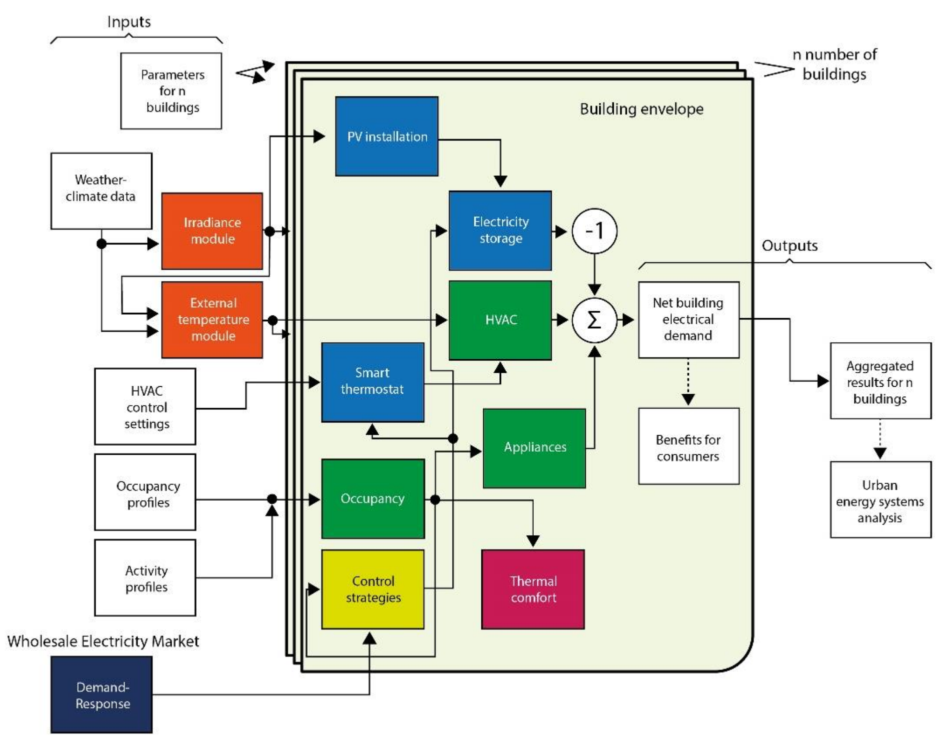

Figure 1. Current architecture of the DREEM model

Requirements

Inputs	Outputs
TMY3 weather data format, as obtained from http://energyplus.net/weather, Building typologies according to Tabula webtool (http://episcope.eu/building-typology/) Thermal comfort parameters, HVAC & control settings, Occupancy & activity profiles	Net building electrical demand, Benefits of self-consumption/demand-flexibility for consumers, Aggregated results for n buildings Benefits/losses for suppliers
Input data in CSV format	**Output data in CSV and MAT formats**
Language: Python source code, Modelica (simulations using Dymola environment)	

Classic decision-making used to be based on a static plan that was considered optimal for the "most likely" future outcome. This approach was proven vulnerable to unexpected future evolutions, which often led to failure of plans that were considered optimal. With dynamic and adaptive policies, the focus is on short-term planning, with simultaneous description of potential future adaptive actions that can be deployed so that the final target is achieved. To do so, AIM evaluates the performance of selected policies over many combinations of a large number of contextual uncontrollable variables (scenarios), visualizes successful policy pathways towards a predefined target, and sets up a monitoring system for real world policy adaptations in case of unexpected contextual future evolutions.

The novelty of AIM lies in: **(i)** using a simple clustering logic, thus it can be easily adapted for soft-linking with a wide variety of models, **(ii)** generating adaptive policies for different contexts, by changing the limits of the uncontrollable variables (scenarios), making it a useful tool for application at various scales and contexts, and **(iii)** facilitating interactive stakeholder consultation for the design of policy pathways, through real-time and easily interpretable visualizations. The exploratory analysis consists of three main modules visually presented in **Figure 2** below. More information is presented in Michas et.al. (2020) [5]

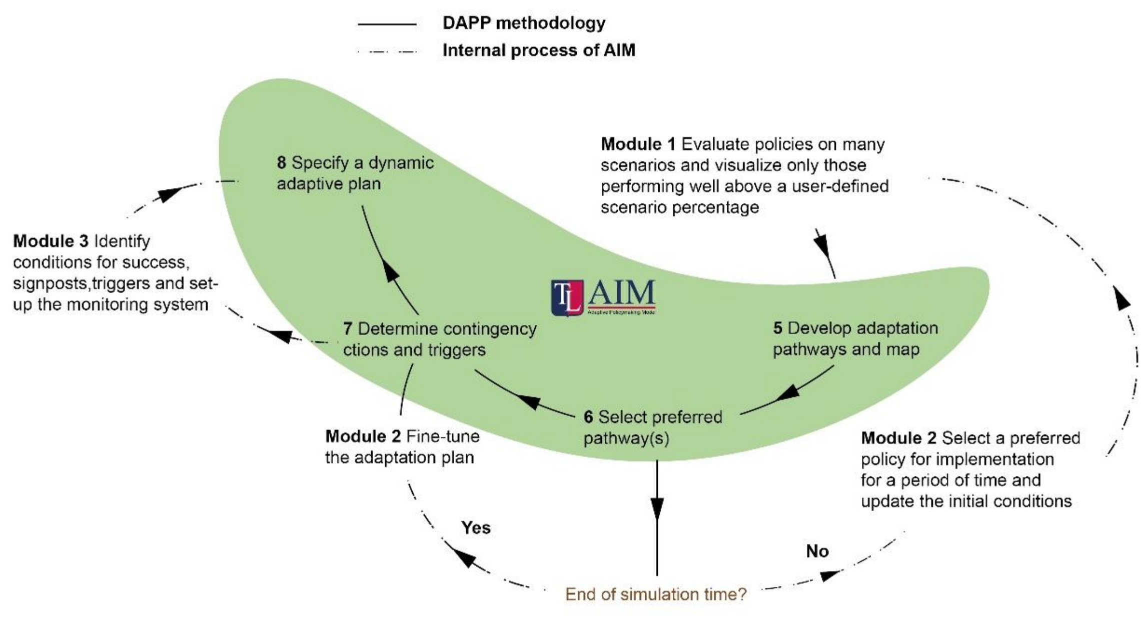

Figure 2. The modules of AIM applied in the context of the original Dynamic Adaptive Policy Pathways (DAPP) methodology

Requirements

Inputs	Outputs
Simulation Models' Inputs-Outputs	Adaptive policy maps
Language: Python source code	

The contribution of the STEEM plugin toolbox to the wider modelling community, lies in:

I. **Fast/interactive model approximations:** This can help establishing a tight loop between stakeholders and the modelling teams, thus making it possible to identify options and scenarios in a timely fashion that stakeholders either reject or explore further in terms of costs or impacts,

II. **Quantifying the uncertainties that govern the modelling assumptions:** Through the relevance-based learning capability of the STEEM, users can evaluate what the most valuable data for the given task are.

STEEM belongs to the framework family; it uses a purely mathematical methodology to emulate the operation of analytical, computationally-complex models, but without the requirement to know the dynamics, physics, engineering and mechanics governing these models.

However, how does the emulator map outputs to inputs without knowing the underlying mathematics?

Black box models are ignorant of the underlying mathematics. They need a two–step approach to use them. The first step is called calibration: inputs and outputs produced from the analytical models are given to the model to train it. Then, the trained model is used to make approximations/predictions, emulating the original model behind the data. Statistical regressions, neural networks and other machine learning methodologies are most often used to train the model and produce approximations. The main advantage of these models is the low computational requirements and consequently the fast simulations. STEEM belongs to the black box category and uses a Gaussian Process (GP) regression for the calibration and prediction procedures [6].

Requirements

Inputs	Outputs
Simulation Models' Inputs-Outputs	Fast/interactive model approximations Quantification of uncertainty
Language: Python source code	

Why TEEM suite?

TEEM is a complete modeling suite that allows users to perform quick simulations as part of an iterative participatory process aiming to provide answers to "***what if***" scenarios. The models can be coupled (i.e., soft- and/or hard- linking) to support the evaluation of the expected impacts from bringing demand-flexibility into the power market and/or to simulate the adoption of technologies that can be regarded as flexibility enablers (i.e., smart-grid devices).

For example, in the context of Greece, the co-simulation of the TEEM suite can shed light on the trade-offs or synergies between a low-carbon transition that relies mainly on large-scale RES plants and a transition that favours small-scale, decentralized RES generation. The inputs/outputs of the co-simulation can be used for deriving a fast, emulated model that can support face-to-face interactions (i.e., workshops, interviews, etc.) with key policymakers and stakeholders in Greece.

Model Application & Indicative Model Outcomes

ATOM – AIM - STEEM

Figure 3 presents the applicability of both TEEM plugin models (AIM and STEEM) coupled with ATOM, in the context of a transdisciplinary modeling framework that generates dynamic adaptive policy pathways supporting the diffusion of small-scale PV installations towards the achievement of the 2030 capacity targets in Greece.

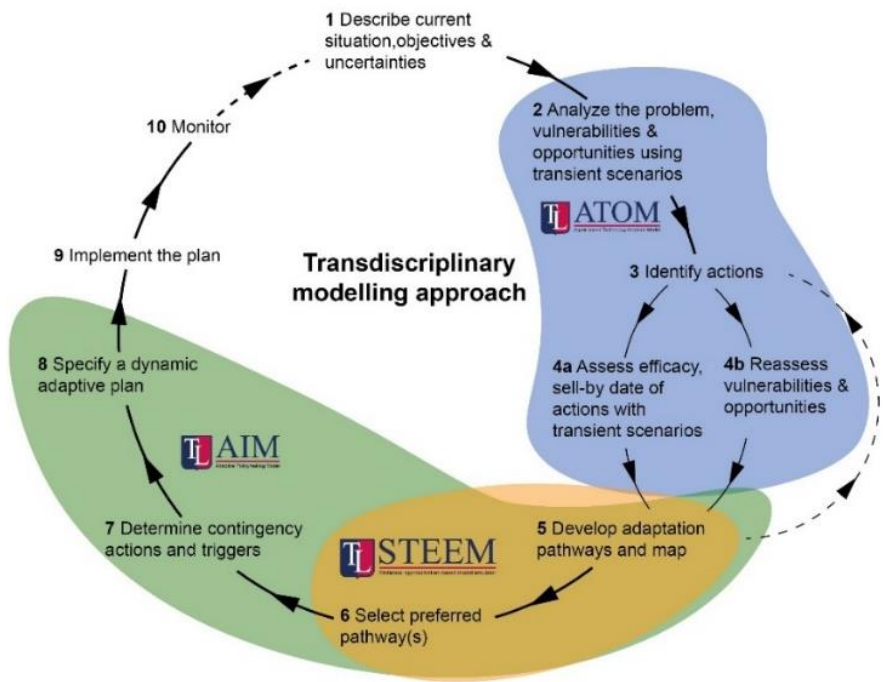

Figure 3. An indicative transdisciplinary modelling framework for the design of dynamic adaptive policy pathways towards the achievement of the 2030 PV capacity targets in Greece

The policies under consideration are the Net-Metering scheme currently operational in Greece and 3 typologies of subsidizing self-consumption with storage (i.e. 30%, 50% and 65% subsidy of the initial battery investment costs). The contextual factors that were used to create the ensemble of uncertainty scenarios for the assessment of the selected policies are: **(i)** the annual increase rate of the electricity retail price, **(ii)** the annual decrease rate of the battery storage investment costs, **(iii)** the annual decrease rate of the PV panel investment costs, and **(iv)** the annual increase/decrease rate of the residential electricity demand, all with reference to 2017 levels. 1000 combinations of the above uncontrollable variables were generated, and each policy scheme was evaluated for all these cases. Policy schemes were considered successful if

i. the PV capacity additions met at least the EU-prescribed intermediate milestones,
ii. the maximum capacity achieved was not above 20% of the trajectory,
iii. for the years without a specific milestone, the PV capacity additions followed the capacity trajectory with an allowed deviation of ±20%.

in more than 70% of the future evolutions (scenarios). The upper limitation was set (in line with stakeholders' advice) to limit policy costs. An indicative policy pathway visualisation is shown in **Figure 4**.

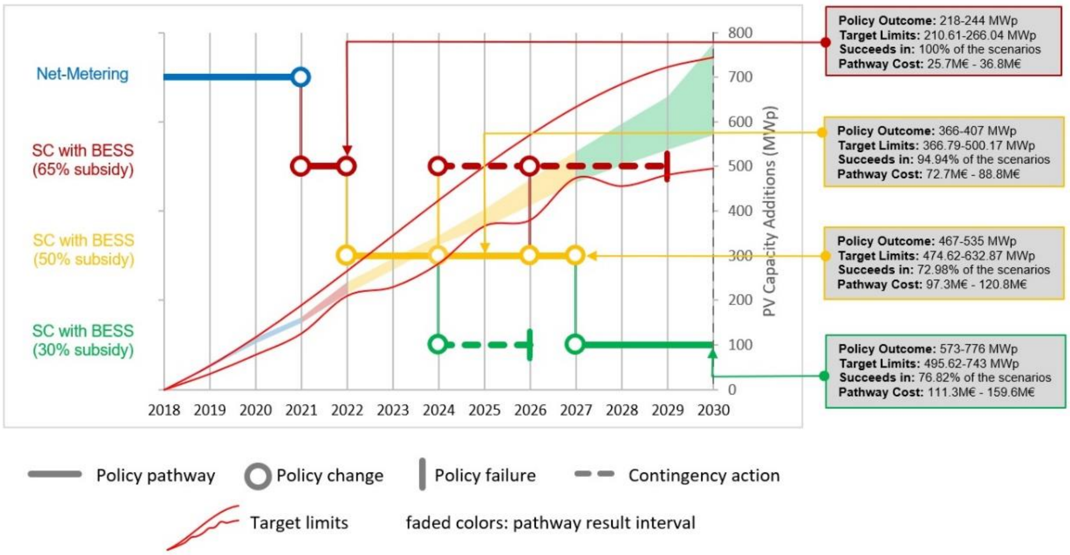

Figure 4. Indicative adaptive policy pathways mapping to explore support towards the achievement of the PV capacity targets for 2025 and 2030 in Greece

Figure 5 shows an indicative trigger point for 2030 which signals the potential need for re-evaluation of policy options, as generated by the monitoring system.

```
_____Target Year: 2030_____
Policy 30% Subsidy is plausible! It achieves the 2030 objective in 76.82%
of the unknown futures
Target 2030: 619.71MW
Average capacity achieved: 670.93MW

The trigger values for the year 2028 are the following:
Surpassing target:
                  min      max     qp values
PV cost rate    -38.65   -18.00   6.96e-20
```

Figure 5. Adaptation Trigger point as generated by the monitoring system of AIM

The min and max trigger point levels shown in the figure, indicate the limits within which the most influential uncontrollable variable(s) should be in 2028 so that no policy change would be required. Out of these (trigger points') levels, a re-evaluation and switch to alternative policies is advisable.

References

Methodological framework and implementation/applications of the models has been presented in the following deliverables of the H2020 project "TRANSrisk"

1. **BSAM:** "D5.3: Appraisal of economic uncertainties associated with climate policy",
2. **ATOM:** "D6.3: Report on investigating agency at firms and individual household levels, including method/ model documentation and analytical findings",
3. **DREEM:** "D6.4: Report describing key characteristics of Innovation Policy Options",
4. **AIM & STEEM:** "D7.3: Toolboxes for adaptation and mitigation policy pathways".

and in the scientific articles below:

[1] Papadelis S, Flamos A, Androulaki S. Setting the framework for a Business Strategy Assessment Model. Int J Energy Sect Manag 2012;6:488–517. doi:10.1108/17506221211281993.

[2] Nikas A, Stavrakas V, Arsenopoulos A, Doukas H, Antosiewicz M, Witajewski-baltvilks J, et al. Barriers to and consequences of a solar-based energy transition in Greece. Environ Innov Soc Transitions 2018;In Press. doi:10.1016/j.eist.2018.12.004.

[3] Stavrakas V, Papadelis S, Flamos A. An agent-based model to simulate technology adoption quantifying behavioural uncertainty of consumers. Appl Energy 2019;255:113795. doi:10.1016/j.apenergy.2019.113795.

[4] Stavrakas V, Flamos A. A modular high-resolution demand-side management model to quantify benefits of demand-flexibility in the residential sector. Energy Convers Manag 2020;205:112339. doi:10.1016/j.enconman.2019.112339.

[5] Michas S, Stavrakas V, Papadelis S, Flamos A. A transdisciplinary modeling framework for the participatory design of dynamic adaptive policy pathways. Energy Policy 2020;In press.

[6] Papadelis S, Flamos A. An application of calibration and uncertainty quantification techniques for agent-based models. In: Doukas H, Flamos A, Lieu J, editors. Underst. Risks Uncertainties Energy Clim. Policy - Multidiscip. Methods Tools a Low Carbon Soc. Springer B. Ser., Springer, Cham; 2019, p. 79–95. doi:https://doi.org/10.1007/978-3-030-03152-7_3.

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