

OMG: A Scalable and Flexible Simulation and Testing Environment Toolbox for Intelligent Microgrid Control

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Summary

Micro- and smart grids (MSG) play an important role both for integrating renewable energy sources in conventional electricity grids and for providing power supply in remote areas (Lund, Østergaard, Connolly, & Mathiesen, 2017). Due to their high efficiency and flexibility, power electronic converters are largely used to drive modern MSG. Power electronics is the application of solid-state electronics to the control and conversion of electric power which is largely performed with semiconductor switching devices such as diodes or power transistors. This includes energy conversion in terms of voltage and current amplitude, frequency and phase angle as well as the number of phases between two or more electrical energy systems to be connected.

Controlling MSGs is a challenging task due to the high requirements on energy availability, safety and voltage quality. This is particularly demanding due to the wide range of different MSG topologies depending on their field of application like industrial campuses, residential areas or remote off-grid electrification (Kroposki et al., 2008). This results in high demand for comprehensive testing of new control concepts during their development phase and comparisons with the state of the art to ensure their feasibility. This applies in particular to data-driven control approaches such as reinforcement learning (RL), the stability and operating behavior of which cannot be evaluated a priori (Garcia & Fernández, 2015).

OMG is a Python-based package for modeling and simulation of microgrids based on power electronic energy conversion. An attached OpenModelica (Fritzson et al., 2018) library enables the user to define their microgrid (i.e. a local electricity grid containing arbitrary sources, storages and loads) in a flexible and scalable way or to use predefined example grids. Due to the component-oriented modeling framework based on OpenModelica, dynamic processes on small time scales are in focus, which allows for accurate control and test investigations during transients and steady-state. This is an essential difference to already available open-source solutions for the simulation of electrical energy networks, which, in contrast, generally depict large-scale transmission networks with abstracted models in the (quasi)-stationary state (e.g. PyPSA (Brown, Hörsch, & Schlachtberger, 2018) or Pandapower (Thurner et al., 2018)). Besides the pure modeling and simulation of microgrids, basic building blocks for setting up a hierarchical control framework on the inner and primary level (Guerrero, Chandorkar, Lee, & Loh, 2013) are provided with OMG.

The API is designed to provide a user-friendly interface to connect a modeled microgrid (the simulation environment) with a wide range of control methods such as classical linear feedback control or model predictive control techniques (cf. Fig. 1). Moreover, the standardized OpenAI Gym interface (Brockman et al., 2016) is also available for training data-driven control approaches like RL. Many auxiliary functionalities for the essential operation of microgrids are shipped with OMG such as coordinate transformations for basic controller classes, monitoring

wrappers and phase-locked loops for frequency and phase angle extraction. Following this structure, nearly every control approach including data-driven RL can be implemented and tested with OMG in a relatively short amount of time. To highlight the challenges of data-driven control approaches in safety-critical environments, application examples using safe Bayesian optimization (Berkenkamp, 2020) for automated controller design are provided in the toolbox.

OMG is designed to be used by academics in the field of control and energy engineering as well as data science. The primary objective of the toolbox is to facilitate entry for new users into the modeling, control, and testing of microgrids and to provide a platform on which different control methods can be compared under defined conditions (benchmarks).

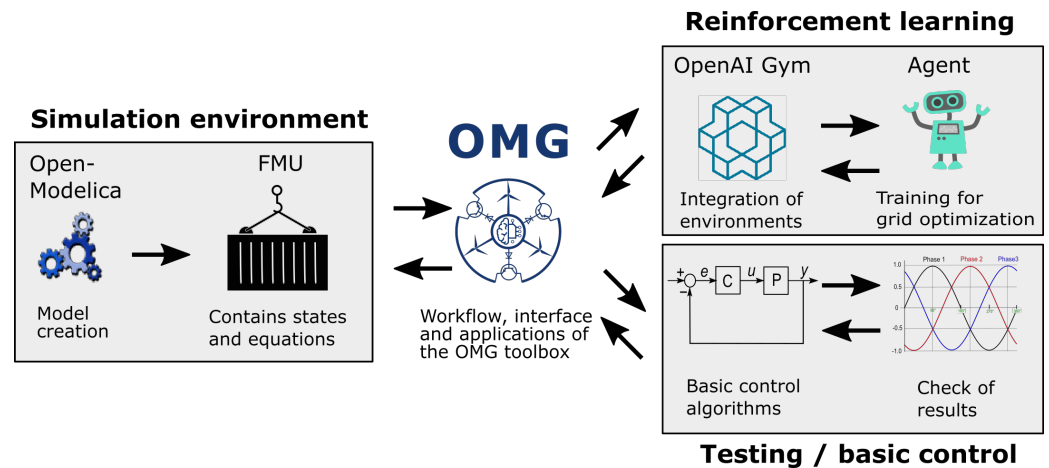


Fig. 1: Overview of the interconnections between the different parts of the OMG toolbox. The OpenModelica and OpenAIGym logos are the property of their respective owners.

Features

The OMG toolbox provides the following key features:

- A library for the scalable and flexible design of local electricity grids in OpenModelica. The user can select between a wide range of different grid components and connect them in a plug and play approach.
- Dynamic simulation of local electricity grids on component level including single and multi-phase systems as well as AC and DC operation.
- Easy exchange of models between computing platforms and simulation of the models by using the FMI 2.0 standard (Modelica Association, 2020) with C++ code inside and PyFMI (Modelon AB, 2020) for the access in Python. Appropriate numeric solvers for the underlying system of ordinary differential equations can be easily chosen within the usual Python packages (e.g. SciPy) due to the usage of co-simulation.
- Calculation, evaluation and monitoring of every single time step covering states, action and auxiliary quantities provides an interface for manual or automated inspection. The latter is particularly useful for the automatic training of data-driven control approaches such as reinforcement learning.
- Many software auxiliaries for the control and monitoring of power electronic-driven microgrids are provided.
- Interesting use cases applying safe data-driven learning to highlight the requirement of safety in a delicate control environment are available.

Examples

Detailed examples are shown in the whitepaper of this toolbox: <https://arxiv.org/pdf/2005.04869.pdf>

Especially the implementation and evaluation of a safe Bayesian controller (Berkenkamp, 2020) is explained in detail. The SafeOpt learning algorithm is applied to an automatic controller tuning problem with safety-relevant state constraints in different microgrid topologies (e.g. different number of inverters, load characteristics). Furthermore, the provided evaluation tools enable the user to compare the performance of different RL algorithm against each other and against manually tuned inverters.

Availability and implementation

OMG is supported and tested on Linux and Windows. The package can be installed with the PyPI, the Python package index, using `pip install openmodelica_microgrid_gym` command. The source code, guide and datasets are available on the GitHub repository (<https://github.com/upb-lea/openmodelica-microgrid-gym>).

Individual contributions of the authors

Following are shown the main fields of each individual contributor of OMG:

- S. Heid: Main software architecture, software module integration, unit tests
- D. Weber: Application examples, control-related auxiliary features (e.g. basic expert controllers), unit tests
- H. Bode: Design of the specific OpenModelica library created for OMG, grid modelling and simulation, data transfer between OpenModelica and Python, unit tests
- O. Wallscheid: Concept design and idea generation, testing and technical feedback, administrative project management
- E. Hüllermeier: Administrative project management, concept-oriented feedback

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