UMONS
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EFES

Building-scale hybrid energy community models for hydrogen, electricity, and heat

UNIVERSITÉ LIBRE DE BRUXELLES

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Wallonie recherche SPW
Cenaero

Context of the project

EFES (Enhanced Flexibility in Energy Systems) is a project funded by Europe and Wallonia which addresses the major challenges posed by the growing electrification of energy systems, particularly regarding storage, conversion, and flexibility management. Bringing together four francophone universities, research partners, and Walloon industrial stakeholders across 13 doctoral theses, EFES is structured around two topics: the first focuses on **energy storage and conversion technologies** (thermal storage, e-fuels, geothermal storage, metal fuels, heat pumps), while the second addresses **energy flow management within energy communities**, covering market design, control and sizing models for multi-sector communities.

Context & Problem of the thesis

Hybrid renewable energy communities (RECs) combining photovoltaics, battery storage, and hydrogen systems (electrolyzer and fuel cell) are a promising solution for local, low-carbon energy autonomy. However, their real-time optimal control is challenging due to strong nonlinearities in key components, such as fuel cell (FC) performance, leading to non-convex constraints and MINLP formulations that are computationally intractable for real-time applications. This work addresses this challenge by developing neural network-based surrogate models of nonlinear components tailored for Model Predictive Control, enabling MILP reformulation that ensures real-time feasibility while maintaining high solution quality and accurate system dynamics.

Proposed approach : Three-layer framework

Physical models
High-fidelity truth model

- **Accurate physics-based modeling**
- **Training data generation for the neural network**
- **Dispatch simulation benchmark**

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NN surrogate
Tractable approximation

- **Train a ReLU neural network**
- **Embed the NN as linear constraints**
- **Reformulate MINLP → MILP for tractable optimization**

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MPC / RHC
Real-time control layer

- **Optimize over a receding horizon**
- **Apply the first control action**
- **Update the horizon and repeat**

Contributions

1. **FC surrogate → MILP**: ReLU NN embedding PEM-FC efficiency for real-time optimization
2. **MPC dispatch**: Receding horizon control with battery + H_2 dynamics
3. **Benchmarking**: MILP vs MINLP vs MILP-NN vs rule-based (quality, time, constraints)

Preliminary Results

Strategy	Solution Quality	Computation Time	Objective Cost
Rule-Based	+++	+++	--
MILP	+++	-	++
MINLP	++	---	+++
MILP-NN	+++	--	+++

Status and next steps

TASK 1
Current focus
Simplified steady-state models for nonlinear technologies
We are here

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TASK 2
Simplified dynamic models for nonlinear technologies

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TASK 3
Models for technologies governed by partial differential equations