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RL3

A Reinforcement Learning Approach for Optimal Control in Microgrids

D. Salaorni, F. Bianchi, F. Trovò, M. Restelli

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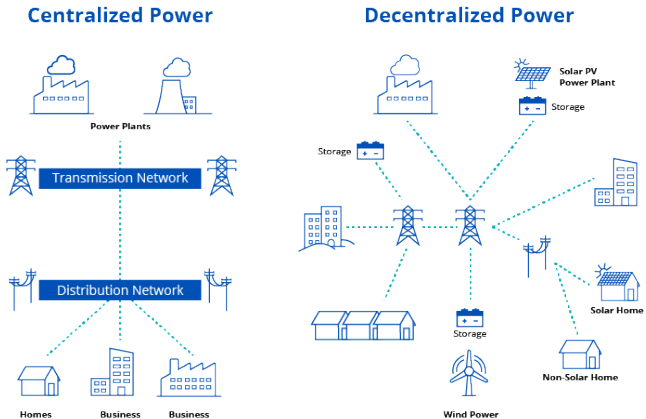
INTERNATIONAL NEURAL NETWORK SOCIETY

International Joint Conference on Neural Network (IJCNN 2025)

Motivation

The Power Grid System



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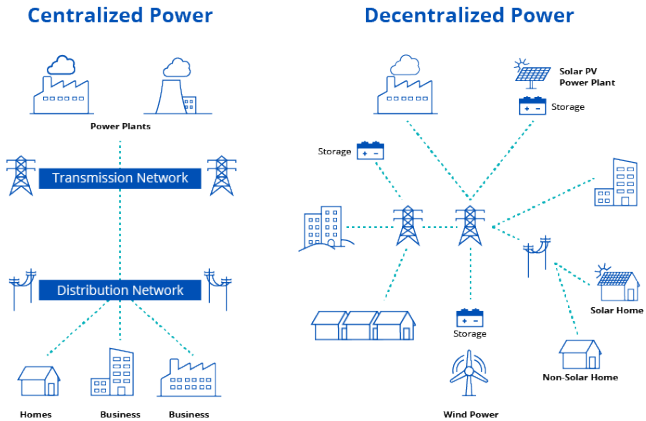
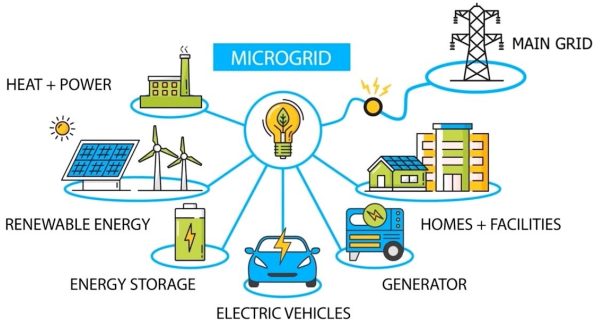


Decentralization $\Longrightarrow$ challenges in energy management

Motivation

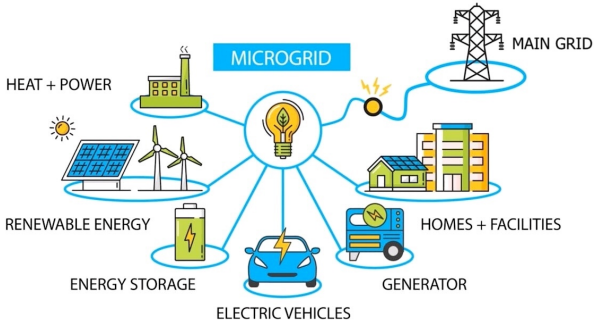
The Microgrid System



Optimize energy management in microgrids means

Motivation

The Microgrid System



Optimize energy management in microgrids means

- Dealing with the **uncertainty** in energy generation and consumption

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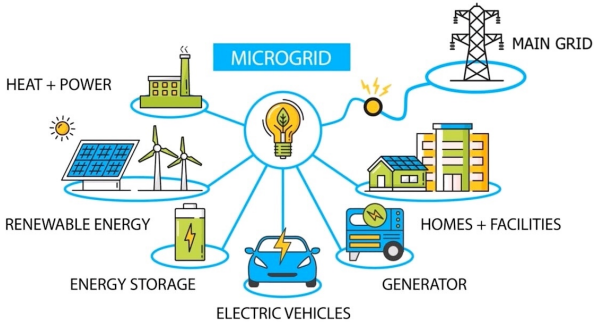

Optimize energy management in microgrids means

- Dealing with the **uncertainty** in energy generation and consumption
- **Minimizing energy-related costs**, which depend on:
  - the **spread** between buying and selling energy prices
  - the **degradation** of the battery and its replacement cost

The Proposed Solutions

From the Literature

- Energy management with **no market prices** (Liu et al. [2021])
- Limited battery simulation with **no degradation costs** (Shojaeighadikolaei et al. [2021], Kolodziejczyk et al. [2021], Domínguez-Barbero et al. [2020], Chen and Bu [2019], Guo et al. [2022])

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- Accurate battery dynamics, but **simplistic aging model** (Sui and Song [2020], Lin et al. [2021])

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- Accurate battery dynamics, but **simplistic aging model** (Sui and Song [2020], Lin et al. [2021])
- Strong assumptions on energy prices, **limited overall realism** (Mussi et al. [2024])

The Proposed Solutions

From this Work

Main Contributions

1. Design of a **Reinforcement Learning**-based control strategy for microgrids
   - integrated with a **Digital Twin** for accurate simulation of battery dynamics
   - equipped with a **battery aging model** to account for degradation costs
   - responsive to **dynamic market prices** and **ambient temperature profiles**

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1. Design of a **Reinforcement Learning**-based control strategy for microgrids
   - integrated with a **Digital Twin** for accurate simulation of battery dynamics
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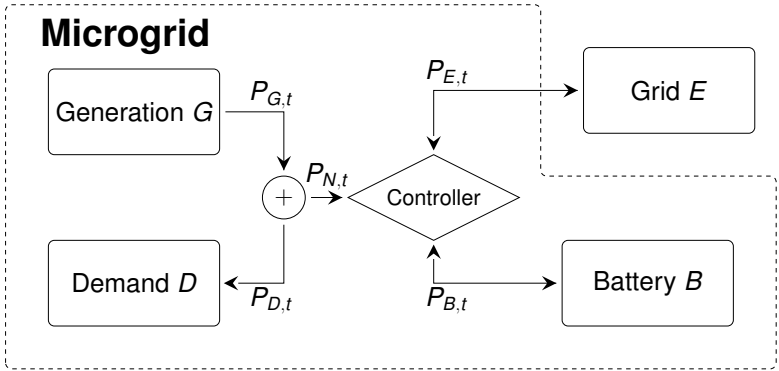
   - responsive to **dynamic market prices** and **ambient temperature profiles**
2. Validation on **real-world** energy datasets

Problem Formulation

The Microgrid Environment



$$P_{N,t} = P_{G,t} - P_{D,t}$$
$$P_{B,t} = a_t P_{N,t}$$
$$P_{E,t} = (1 - a_t) P_{N,t}$$

Problem Formulation

Objective Function

The objective R_T is the **maximization of the cumulative profit** over the time horizon T

Objective

$$R_T(\pi) = \sum_{t=1}^{T} \left[r_{\text{trad}}(a_t) + r_{\text{deg}}(a_t) \right]$$

- $r_{\text{trad},t}$ represents the **trading revenue** at time t
- $r_{\text{deg},t}$ is the **degradation cost** at time t ($r_{\text{deg},t} < 0$)
- π is the strategy adopted and a_t the corresponding action at time t

RL Problem Formulation

Markov Decision Process

MDP

$$\mathcal{M} = (\mathcal{S}, \mathcal{A}, P, R, \gamma, \mu_0)$$

RL Problem Formulation

Markov Decision Process

MDP

$$\mathcal{M} = (\mathcal{S}, \mathcal{A}, P, R, \gamma, \mu_0)$$

- $s_t \in \mathcal{S}$:
  - internal battery state (state of charge, temperature)
  - energy demand / generation estimates
  - market prices
  - seasonal / time-of-day encodings
- $a_t \in \mathcal{A}$: percentage of $P_{N,t}$ addresses with the battery
- $R : \mathcal{S} \times \mathcal{A} \to \mathbb{R}$ reward function

$$r_t = r_{\text{trad}}(s_t, a_t) + r_{\text{deg}}(s_t, a_t) + \lambda r_{\text{clip}}(s_t, a_t)$$

Learning Procedure

Algorithm

Requirements of the algorithm:

- Profiles of demand, generation, market prices and ambient temperature
- A battery DT

Learning Procedure

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For each step of the episode:

1. Estimate $P_{G,t}$ and $P_{D,t}$
2. Observe state s_t
3. Choose action $a_t \sim \pi(s_t)$
4. Compute $P_{B,t}$ and $P_{E,t}$
5. Update the virtual battery (simulated with the DT)
6. Collect reward r_t
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Until convergence to π^*

Experimental Campaign

Experimental Setting

- Offline data (2015–2020):
  - 398 Italian household demand profiles
  - generation profiles from 3KW photovoltaic panel with Italian irradiation factor
  - Italian energy market prices
  - average Italian ambient temperature profiles
- Environment simulated with ErNESTO Digital Twin [Salaorni, 2023]

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- Environment simulated with ErNESTO Digital Twin [Salaorni, 2023]
- Offline RL agent based on PPO [Schulman et al., 2017]

Experimental Campaign

Baselines

Rule-based:

- OnlyGrid (OG)
- BatteryFirst (BF)
- 20-80, 80-20, 50-50

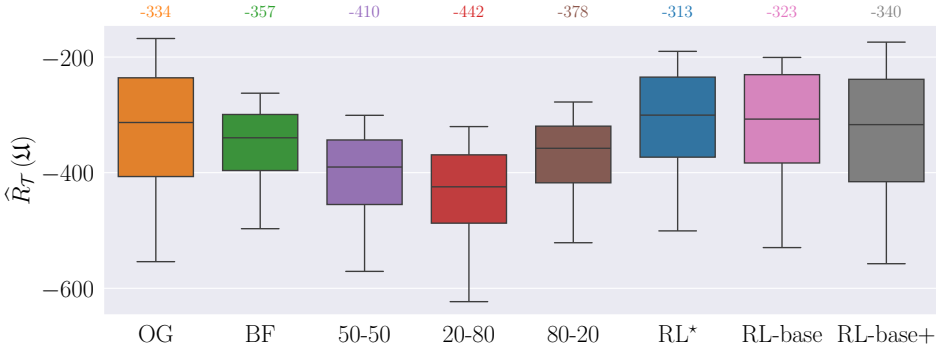
RL-based:

- RL-base: fixed energy prices, no ambient temperature (Mussi et al. [2024])
- RL-base+: dynamic prices, no ambient temperature

Our method: RL*

Experimental Campaign

Return Comparison



- Paired t-test to check if the difference in rewards between *RL** and other methods is significantly greater than zero yielded an overall p-value of 0.0052, indicating strong statistical evidence that our method consistently outperforms the others

Experimental Campaign

Robustness Test

Tests to further corroborate our results:

- Variation of energy **market spread**
- Variation of battery **replacement cost**

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$\Longrightarrow$ **RL*** remains the top performer

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$\Longrightarrow$ **RL*** remains the top performer

Ablation studies on λ term, used to weight the clipping penalty

Conclusions

Outcomes of this work:

- Novel RL-based formalization of microgrid energy management
- Broad experimental campaign based on real-world data
- **RL*** outperforms state-of-the-art and rule-based controllers

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- Novel RL-based formalization of microgrid energy management
- Broad experimental campaign based on real-world data
- **RL*** outperforms state-of-the-art and rule-based controllers

Future works:

- Application to a multi-agent setting (multiple microgrids, renewable energy communities, etc.)
- Design of specific MDP formulations for the presented setting

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Thank you!

Questions?

ErNESTO-gym: check out this work

Gym4ReaL: real-world RL benchmarks

Learning Procedure

Pseudocode

Algorithm 1 Interaction between Agent and Environment

Initialize: s_0, $\{\mathcal{P}_D^{(i)}\}_{i=1}^{M}$, $\mathcal{P}_G$, $\mathcal{C}_{buy}$, $\mathcal{C}_{sell}$, $\mathcal{K}$, $B(\cdot)$, $\pi(\cdot)$
for $j \in \{1, \ldots, n_{ep}\}$ **do**
    Sample demand profile $\mathcal{P}_D^{(i)} \sim Unif\big(\{\mathcal{P}_D^{(i)}\}_{i=1}^{M}\big)$
    Initialize σ_1, T_1, ρ_1
    for $t \in \{1, \ldots, \mathcal{T}\}$ **do**
        Compute estimates $\widehat{P}_{G,t}, \widehat{P}_{D,t}^{(i)}$
        Observe current state s_t
        Agent takes action $a_t \sim \pi(s_t)$
        Compute $P_{B,t} \leftarrow a_t(P_{G,t} - P_{D,t}^{(i)})$
        Update $(\sigma_{t+1}, T_{t+1}, \rho_{t+1}) \leftarrow B(\sigma_t, T_t, K_t, P_{B,t})$
        Compute $P_{E,t} \leftarrow (1 - a_t)(P_{G,t} - P_{D,t}^{(i)})$
        Collect reward r_t
        Update policy $\pi(\cdot)$

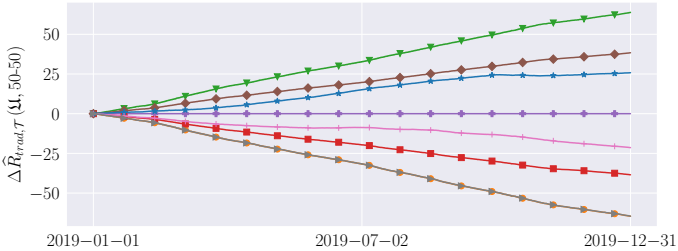
Reward Function

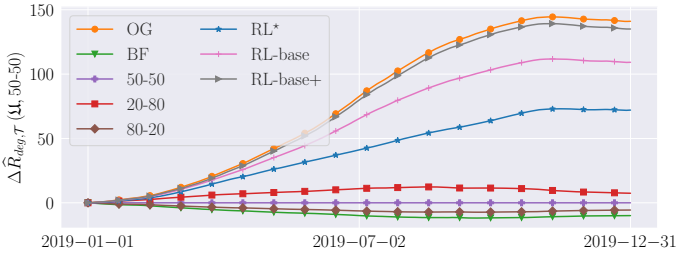
Reward Components

$$
\begin{aligned}
r_{\text{trad}}(a_t) &= (p_t^{sell} P_{E,t}^{+} + p_t^{buy} P_{E,t}^{-}) \Delta\tau \\
r_{\text{deg}}(a_t) &= \frac{\rho_t - \rho_{t-1}}{1 - \rho_{EOL}} \mathcal{R} \\
r_{\text{clip}}(a_t) &= -\max\left\{0, a_t P_{N,t} + \frac{(\sigma_t - \sigma_{\max})}{\Delta\tau} C_t V_t, \frac{(\sigma_{\min} - \sigma_t)}{\Delta\tau} C_t V_t - a_t P_{N,t}\right\}
\end{aligned}
$$

Experimental Campaign

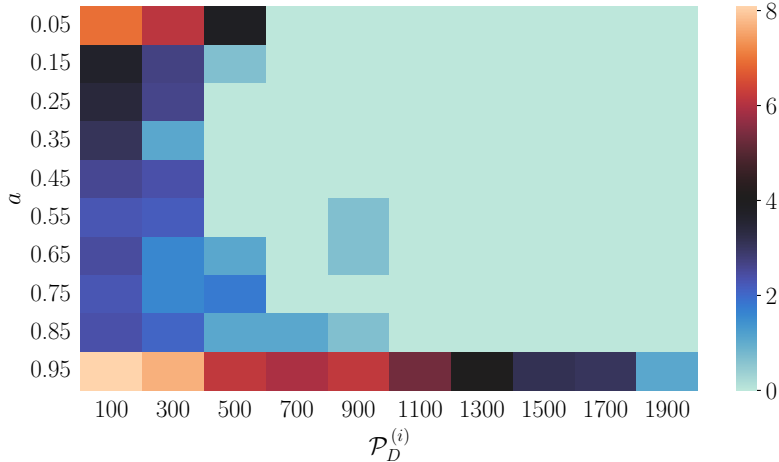
Trading vs Degradation





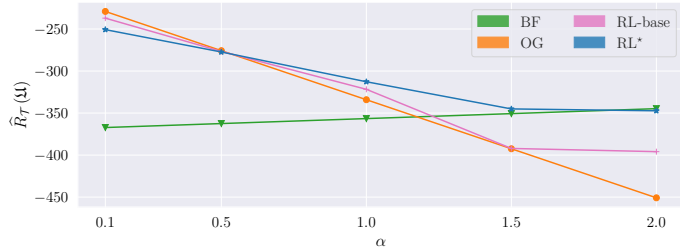
Experimental Campaign

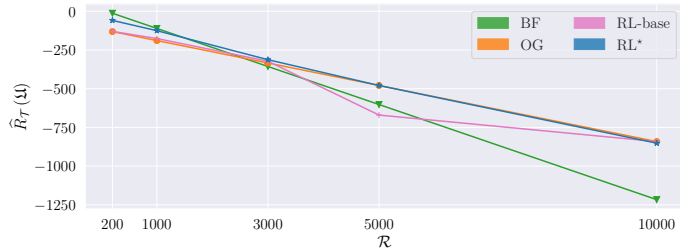
Policy Behavior



Experimental Campaign

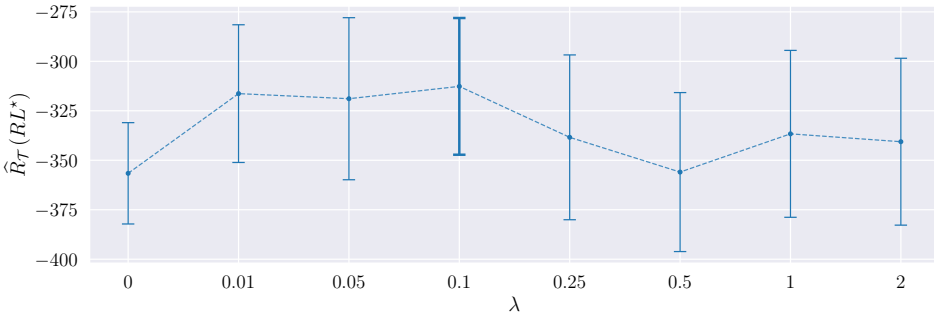
Robustness Test





Experimental Campaign

Ablation Studies



Experimental Campaign

Training Hyperparameters

Parameter	Value
# Episodes	100
# Envs	8
Policy Network Size	$[64, 32]$
Gamma	0.99
Learning Rate	$5e{-}5$
Batch size	512
# Epochs	10
Rollouts	8912
Initial log. std.	-1
Normalize obs.	True
Seed	42