



# FRAUNHOFER INSTITUTE FOR SOLAR ENERGY SYSTEMS ISE

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# Improving Microgrid Autonomy with Reinforcement Learning Electric Vehicle (Dis)Charging Algorithms

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# INTRODUCTION

The flexibility of microgrid energy dispatch can be improved by using EVs as storage devices that can consume intermittent renewable energy generation surpluses and then re-inject this energy at a later time. We apply reinforcement learning (RL) based methods to the distributed, EV-enabled load balancing problem inherent to this strategy. We observe the performance of EV charging/discharging controllers that use RL to decide its power flow set-point for every minute of its EV's scheduled charging/discharging session.

# METHODOLOGY

- Microgrid load profiles were simulated with Fraunhofer's synPRO simulation tool developed in Python
- synPRO generates simulation traces of power systems components with a stochastic bottom-up approach, using real usage data and realistic models
- EV charging controller programmed in Python, runs concurrently with EV battery simulator running in synPRO; REST API used to exchange state information and set point commands

# Reinforcement Learning Enabled EV (Dis)Charging

#### **Markov Decision Process Perspective:**

- The environment is the EV and power system, while the agent is the charging controller
- Every minute, the EV charger must update its charging set point; this update is considered the **action** that the agent is taking
- The state of the environment consists of the EV's SOC, time of day, time remaining in charging session, and EV's most recent PV energy allocation
- **Reward** is characterized as the net amount of local energy that the agent consumes as a consequence for the past minute's charging set point decision.

## **Reinforcement Learning Implementation:**

- Used **Expected SARSA** reinforcement learning method, an off policy, model free, temporal difference (TD) based method
- Leveraged value function approximation techniques to handle multi-dimensional, continuous state-action space
- Enhanced performance with domain knowledge by designing an **action preference function** to prohibit invalid actions in certain states



# SYSTEM MODEL

- Energy community of five apartments with energy consumption habits typical of their subtype
- Four electric vehicles of differing models, and thus different energy needs and charging/discharging characteristics
- Community serviced by combination of main electrical distribution system and local PV distributed energy resource
- PV generation output modelled after a real PV plant in Freiburg recorded in the year 2013; The PV signal was scaled to have a 15.85 kW peak generation capacity, which made its total generation over the entire year

## RESULTS

# Self Sufficiency **Definition:**

Local PV Energy Consumed Total Energy Consumed

#### Mean Day Curve **Definition:**

A power curve where every data point represents the average power consumption at that point in time observed throughout the experiment

#### **Experiment & Outcome**

Trained agents on one year's worth of simulation data, then observed its performance on a new year's worth of data





#### 20,000 kWh.

- Considered two scenarios for smart grid communications infrastructure • Case 1: Smart meters report minute-scale price signal to EV controllers
- Case 2: Also have aggregator node to prevent surplus EV discharge

Type	Subtype	Peak kW	Annual kWh
PV		15.84	20,000
Apartment	Family (1 Child)	7.22	3,532
Apartment	Family (2 Children)	7.72	4,806
Apartment	1 Full Time Worker	5.07	1,766
Apartment	1 Full Time Worker	6.86	2,065
Apartment	2 Pensioners	5.86	2,848
EV	Tesla Model X P100D	22	2,340
EV	Opel Ampera	11	1,319
EV	<b>Opel Ampera</b>	11	849
EV	Renault Twizy	3.7	475

Scenario 1 (charge only) increased overall self sufficiency from 28.4% to 34.8% (6.4% increase)

Scenario 2 (charge and discharge) increased overall self sufficiency from 28.4% to 45.1% (16.7% increase)

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