accenture

Optimizing Energy Balance in Multi-Energy Microgrids

Enhancing Grid Efficiency: Utilizing Deep Reinforcement Learning for Efficient Distribution of Local Renewable Energy Resources

Thesis defense by Tessel Kaal

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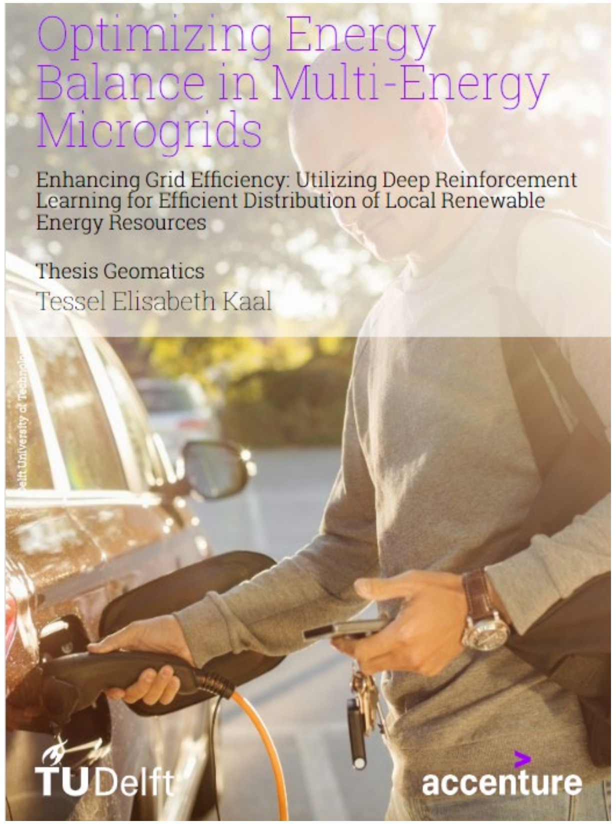
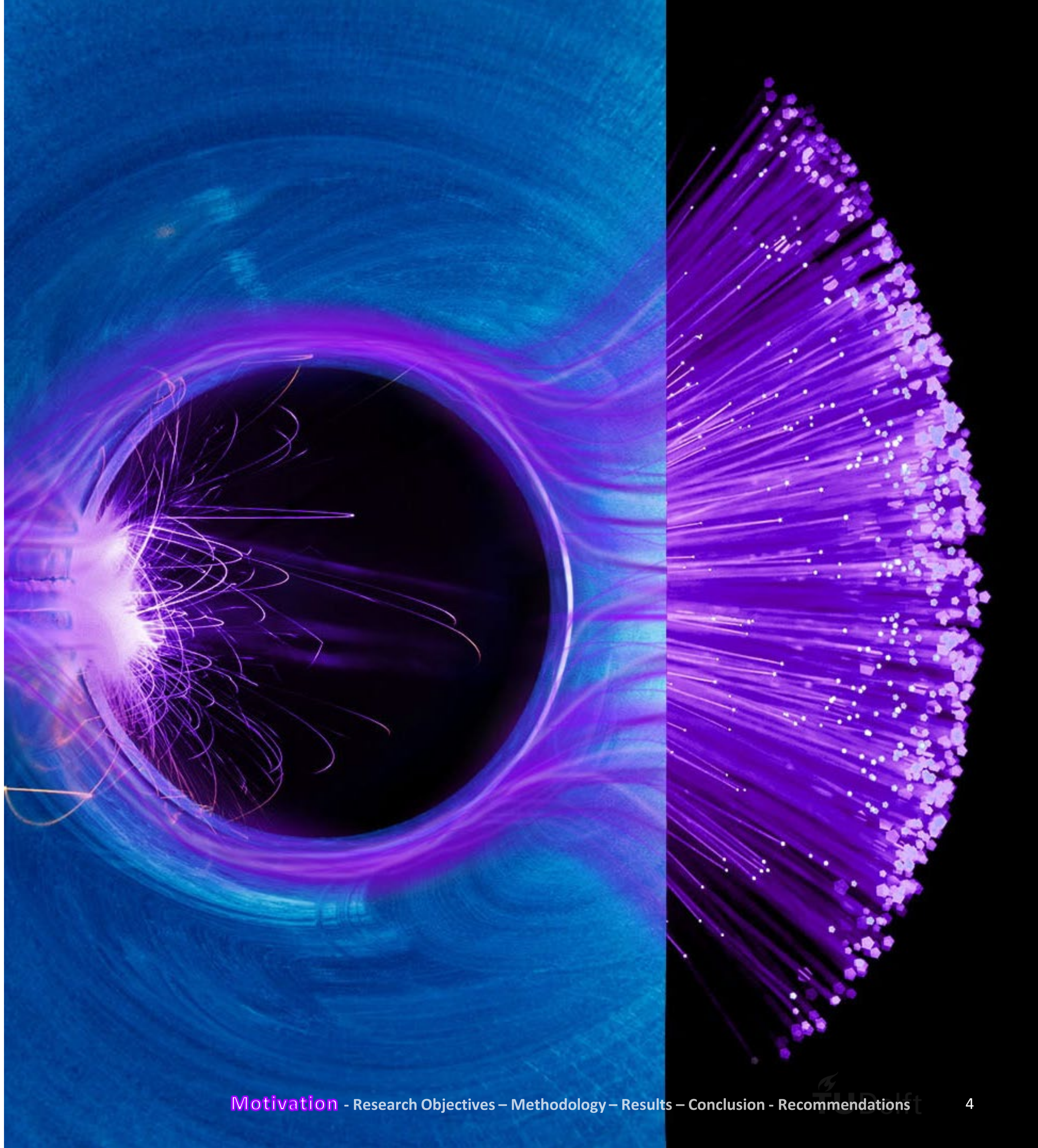
Guiding you through the research



01 Motivation

An energy gap is foreseen

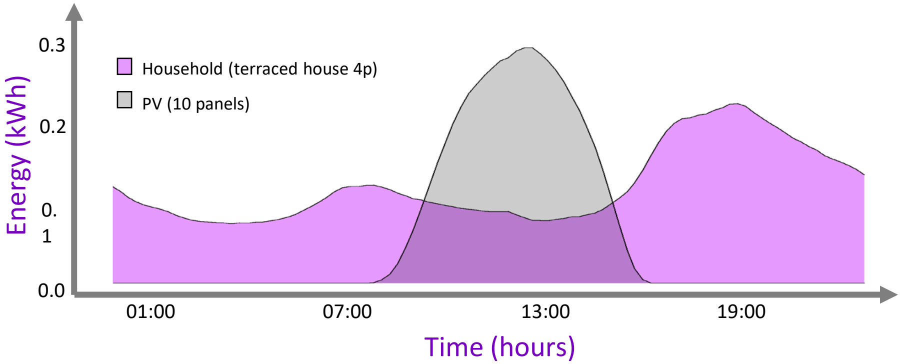
Source: EBN (2024)

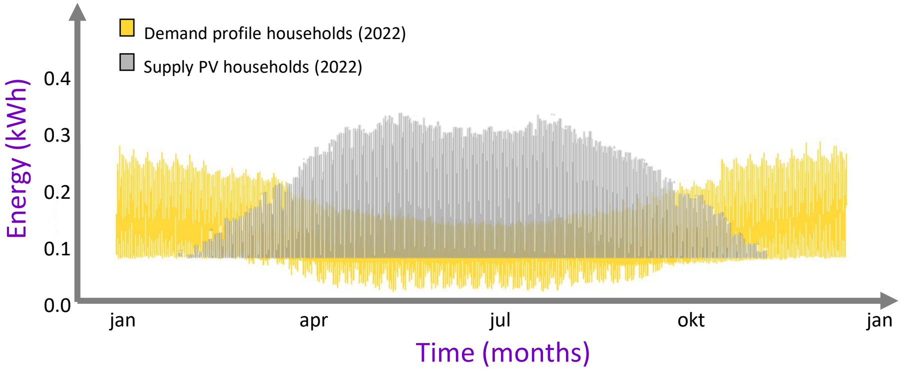


Pressure on the Grid

Increase in Solar/Wind Energy production leads to mismatch based on **time** and **space**

Daily and annual mismatch in solar production and demand among households



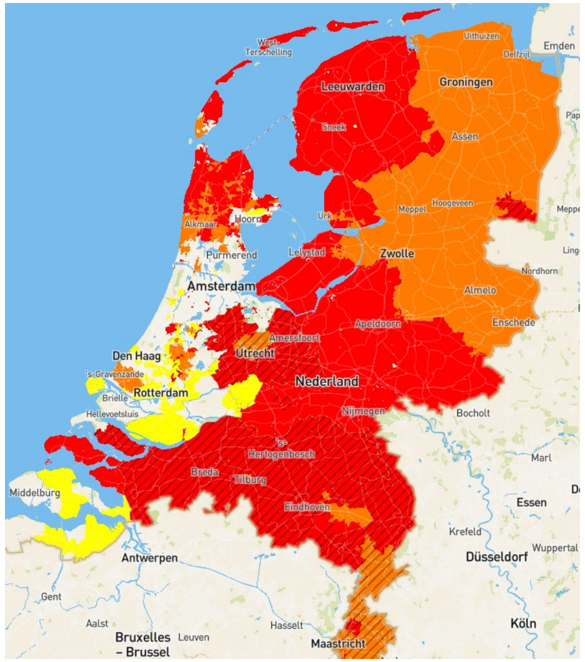


Source: Accenture (2024)

Spatial mismatch between production and supply

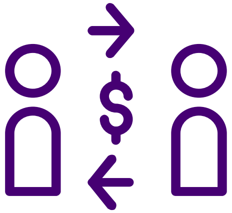
Congestion in the Netherlands in the future

These two problems combined with the current state of the grid lead to congestion



- Transparent: (still) no congestion
- Yellow: Threat of congestion
- Orange: Advance notice of structural congestion at ACM
- Red: Structural congestion

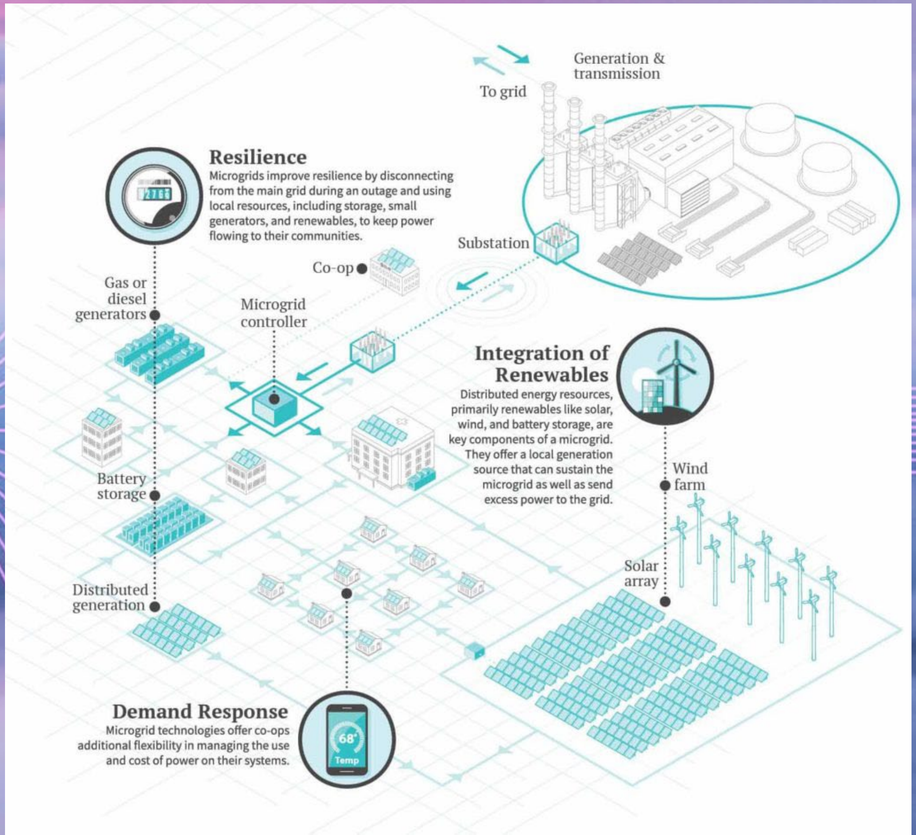
Source: Netbeheer Nederland (2024), Accenture (2024)



Especially at **low voltage level,** the available flexibility options will often not be able to (cost-effectively) reduce the demand peak below the level at which grid reinforcement is no longer necessary.

TenneT

"TenneT expects structural grid congestion until 2029." – TenneT website



Source: NRECA (2024)

Microgrids?

Microgrids or **Energy Hubs** are hot topic

- "A small-scale power subsystem comprising a limited number of DERs, which can include both renewable and conventional energy sources. " (Uddin et al., 2023)
- Can decrease demand from the main grid

Operational Flexibility

Environmental Benefits

Enhanced Grid Reliability

MGs are instrumental in evolving power grids towards greener and more adaptable systems

Challenges Microgrids

What are the challenges when trying to implement and manage MGs?

Optimization of Energy Management

Technical Complexities

Long-term Strategic Planning

*Each type of microgrid can face **unique challenges** based on its design, scale, and the specific needs it serves.*

Energy Grid: The gap

The gap and infrastructure combined form a problem

- Current research underrepresents
  - Urban environments with diverse user profiles
  - Balancing of energy among different functions
  - Case studies often isolated environments

- Location and geographical data approach

- Research should aim to facilitate stakeholders with knowledge towards implementation

How to approach urban Microgrid Energy Management (MEM) problems with RL?

⬇

How can Distributed Energy Resources be deployed and managed, in a cost-effective manner, within an electrified microgrid to achieve a balance between energy consumption and production in order to minimize the burden on the central grid given fluctuating demand?

Research objectives

- deployed and managed .. cost-effective, .. to achieve equilibrium .. , to minimize the burden on the central grid given fluctuating demand -

Release burden on main grid

Improve the cost efficiency

While utilizing intermittent energy sources.

Methodology

Research overview

CONCEPTUALIZATION

- Detail components, relations and interconnections
- Define performance indicators and entities
- Define scenarios for model testing

MODEL ARCHITECTURE

- Translate conceptualizations into quantitative constraints and objectives
- Select programming language and environment
- Select RL algorithm

IMPLEMENTATION MODEL

- Formalize the model architecture and translate the architecture into a functional system
- Employ RL in the model
- Create scenarios

VISUALIZATION MODEL

- Map the physical grid attributes into a digital representation
- Design POC visualization based on user requirements

ANALYSIS AND VALIDATION

- Align results with expectations to validate the agents’ performance
- Analyze and validate results based on convergence and variability

Case study

Kop van Zuid: Big buildings and naturally isolated

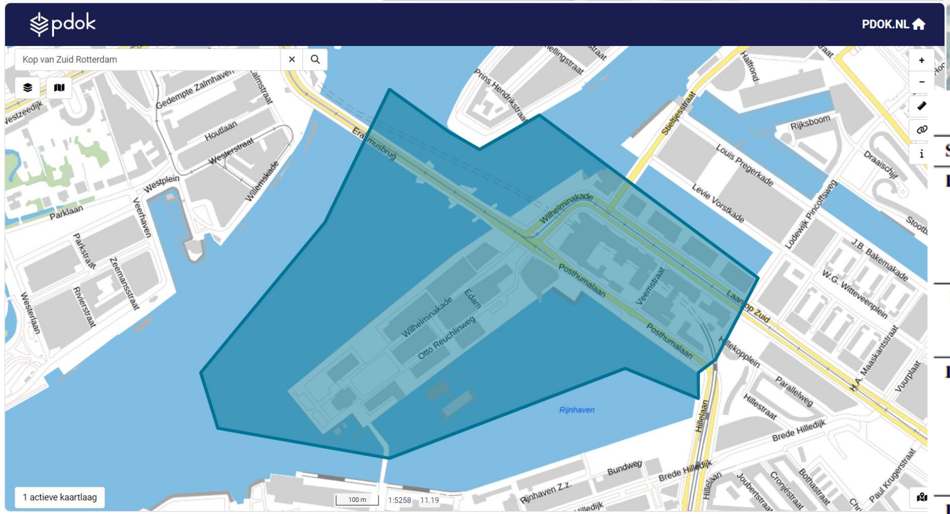


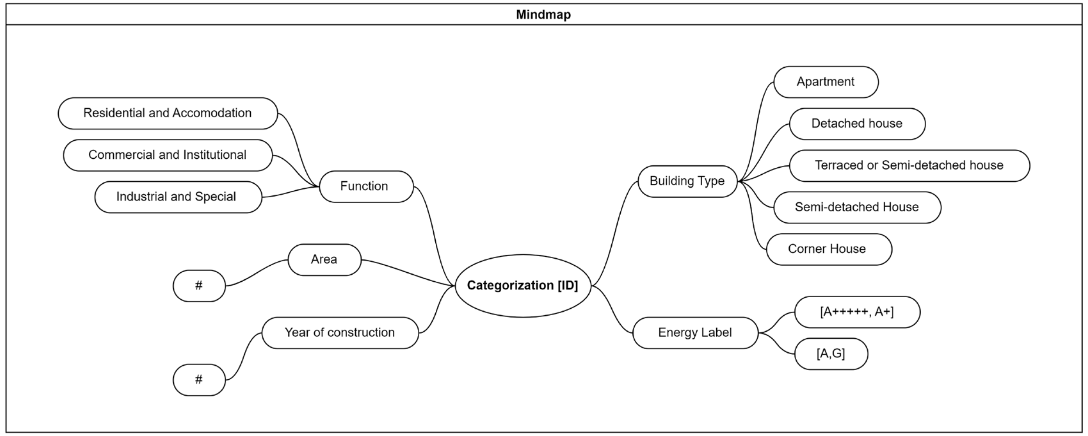
Table 3.2: Summary of energy system scenarios

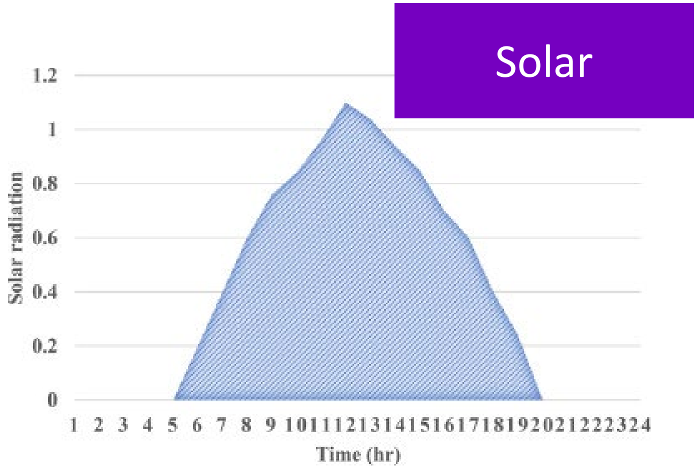
Scenario	Description
Base case	This scenario serves as the control setup, where the current energy system configuration is used without any modifications. The focus here is to establish a benchmark for performance comparison.
Demand side decrease	In this scenario, variations in demand patterns are introduced to evaluate how changes in consumer behavior affect system performance.
Increase in Renewable Energy supply	This scenario explores the impact of varying renewable energy supply sources. It considers the effects of utilizing a single type of renewable energy versus a combination of multiple sources, thus providing insights into the benefits of diversifying energy supply.
Increase in (EV) battery storage possibilities	This scenario examines the role of ESSs in enhancing grid resilience and efficiency. It assesses how different storage capacities and technologies can optimize overall system performance.

Case study: Data acquisition

Synthetical creation of demand profiles for the case study based on open source geographical information

- Case study information
  - Demographic information
- Simulated loads with categorization buildings
- Other Exogenous variables
  - Solar data (timely)
  - Wind data (timely)
  - Geothermal potential
  - Grid costs (timely)





Deep Reinforcement Learning

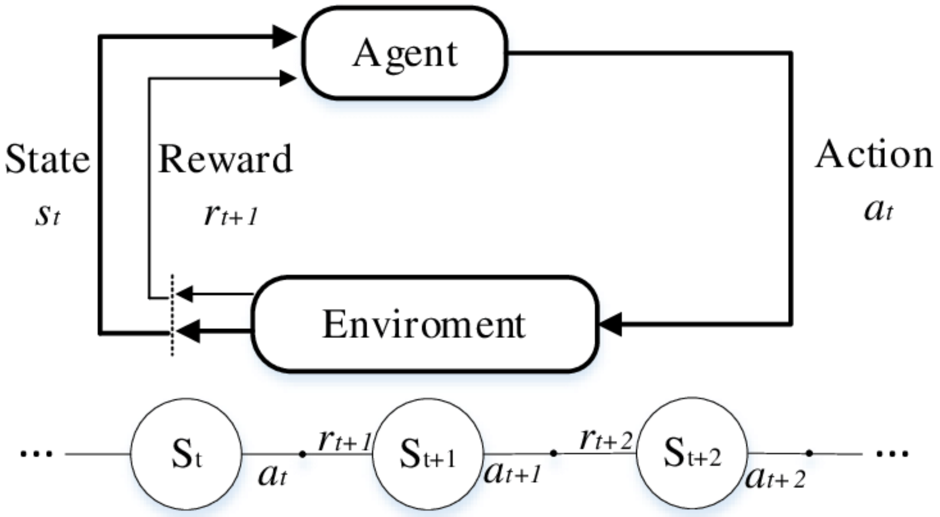
An Algorithm that must be trained, like a child or in this case an **Energy Management system**

How does Reinforcement Learning work?

”The uncertain nature of the microgrid components and the high dimensionality of their variables incentivizes the use of intelligent learning-based methods in the EMS, ***such as DRL algorithms.*** *“*

States and actions:

- (EV) Batteries: charging, discharging, idle (max charge, max discharge)
- Main Grid: importing, exporting, idle (max import, max export)



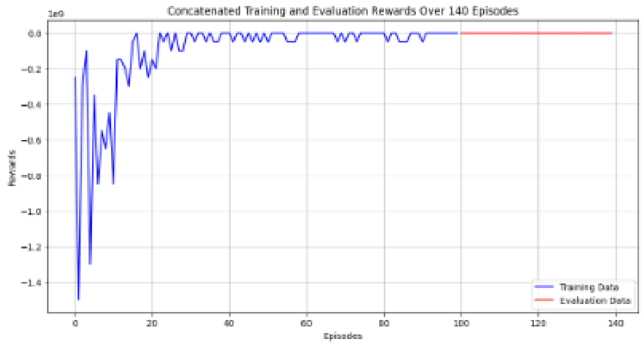
Environment & Reward function

Implementation of the model architecture

- Environment per scenario:
  - Base case is formed based on advancements within the spatial limits
- Reward function:
  - Maximizing independency
  - Minimizing costs

Output

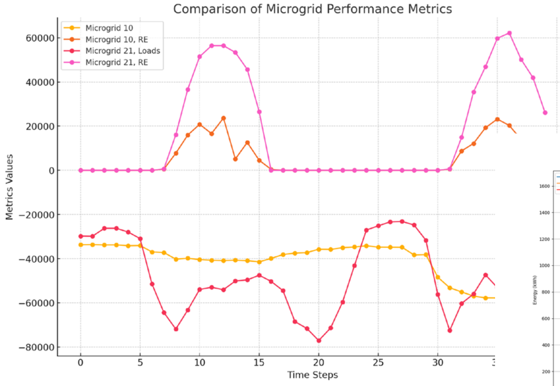
Graph reward function per episode (trainingscurve) & action per timestep

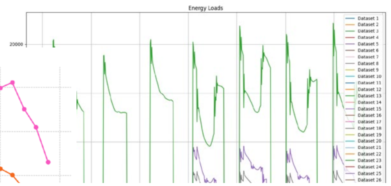


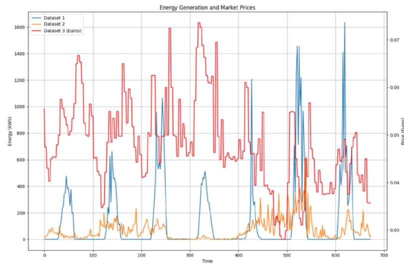
(a) Training curve for environment with base parameters and the loads with a factor 0.2

Data model

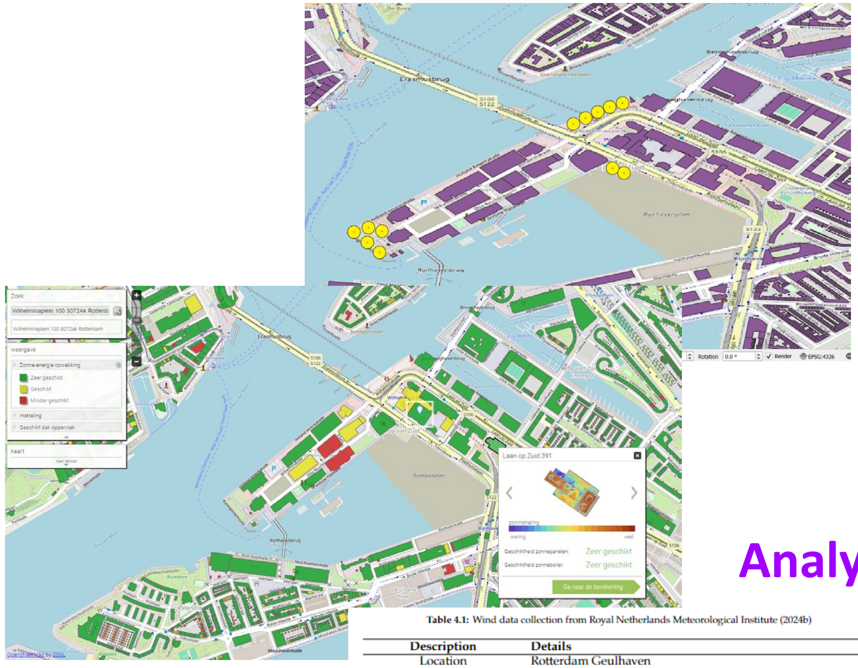
Combination of gathered, and simulated data







Input data



Analysis

Table 4.1: Wind data collection from Royal Netherlands Meteorological Institute (2024b)

Description	Details
Location	Rotterdam Geulhaven
Coordinates	51.891944, 4.3125
Data Collection Frequency	Every ten minutes
Variable: FF_SENSOR_10	Avg. wind speed from sensors 1 and 2 at sensor height (m/s).

Table 4.2: Solar data collection from Royal Netherlands Meteorological Institute (2024a)

Description	Details
Location	Rotterdam Locatie 24
Coordinates	51.960556, 4.446944
Data Collection Frequency	Every ten minutes
Variable: Q_GLOB_10	Avg. radiation (W per m²)

Table 6.2: Variables, parameters, and values DRL model

Variable	Parameter	Value
Small Batteries		
C_{max}	Capacity	500 kWh
P_{charge}	Charge Power	38 kWh
$P_{discharge}$	Discharge Power	38 kWh
η_{ch}	Charge Efficiency	0.9 (dimensionless)
$Cost_{cycle}$	Cycle Cost	\$0.20
$Quantity$	Number of Units	6
Big Batteries		
C_{max}	Capacity	700 kWh
P_{charge}	Charge Power	50 kWh
$P_{discharge}$	Discharge Power	50 kWh

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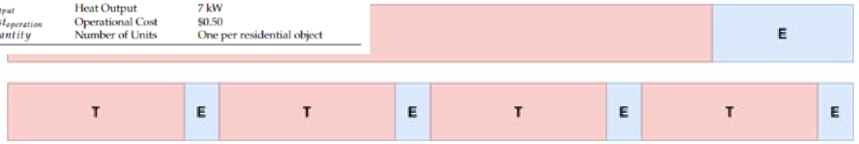
Table 6.2 – continued from previous page

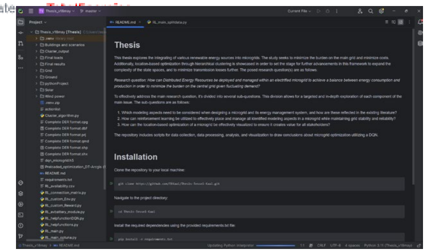
Variable	Parameter	Value
η_{ch}	Charge Efficiency	0.9 (dimensionless)
$Cost_{cycle}$	Cycle Cost	\$0.50
$Quantity$	Number of Units	11
Solar panels		
η_{PV}	Efficiency	0.9 (dimensionless)
$Area_{available}$	Available Area	Solar analysis with Energy atlas, now 0.6 percent
$Quantity$	Coverage	Every available surface
Domestic-scale wind turbines		
$R_{turbine}$	Radius	9 m
C_p	Power Coefficient	0.45 (dimensionless)
ρ_{air}	Air Density	1.225 kg/m³
$Required\_radius$	Free Radius	27 m
$Quantity$	Number of Units	12
Heat Pumps		
P_{input}	Electrical Input	2 kW
E_{geo}	Potential	0.71
COP	Coefficient of Performance	4.5 (dimensionless)
P_{output}	Heat Output	7 kW
$Cost_{operation}$	Operational Cost	\$0.50
$Quantity$	Number of Units	One per residential object



Input parameters

Total-RD/**pymgrid**

pymgrid is a python library to generate and simulate a large number of microgrids.

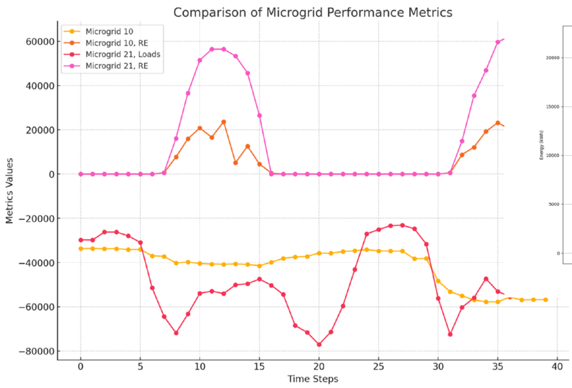


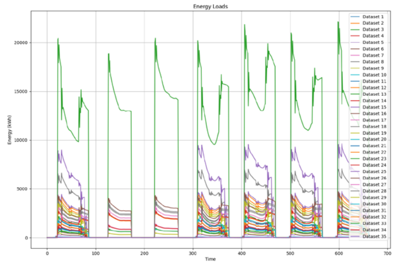
DQN model

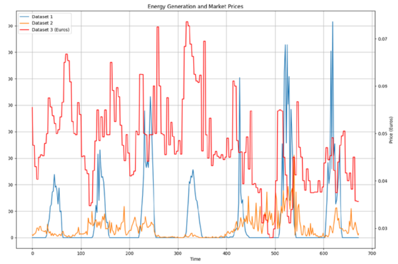
Results: Optimization

Data model

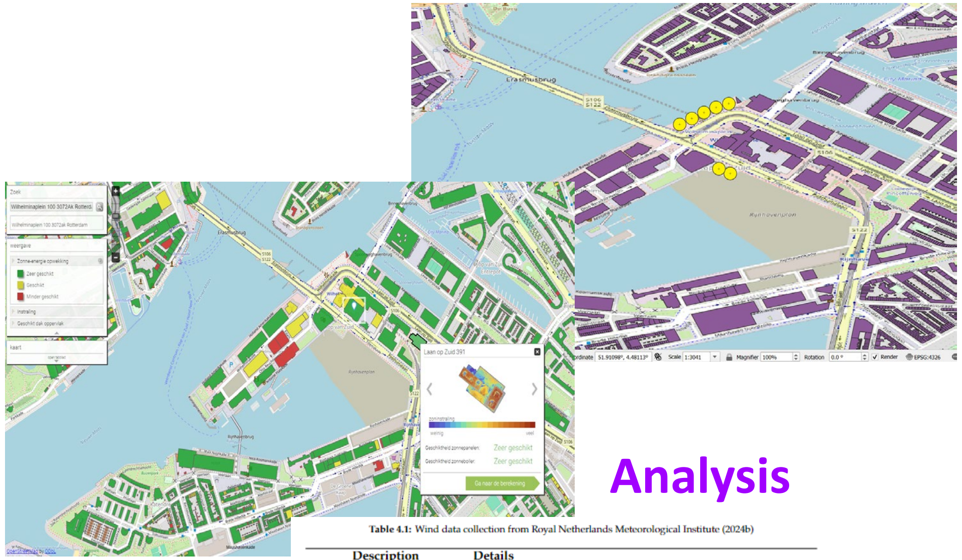
Combination of gathered, and simulated data







(Test) Input data



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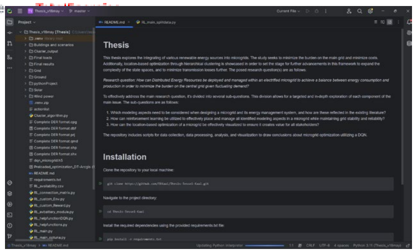


DQN model

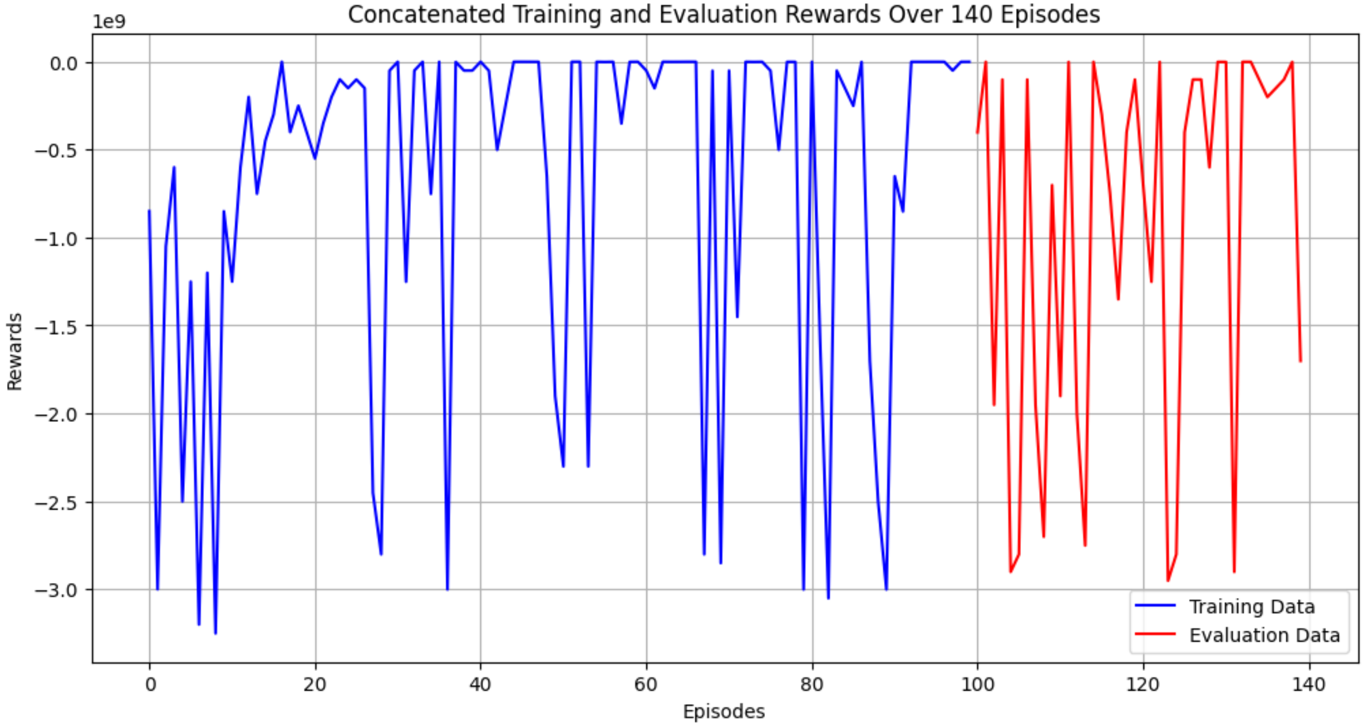
Results Scenario 1 – day patterns

Base case – Trained on 100 episodes and evaluated over 40 episodes

Input

Result

Output Base case



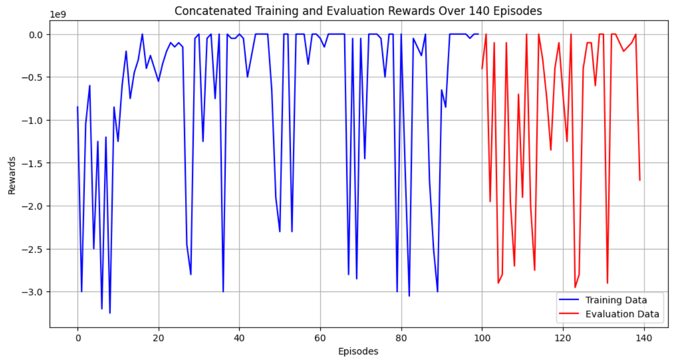
Results Scenario 1 – week patterns

Base case – Trained on 100 episodes and evaluated over 40 episodes

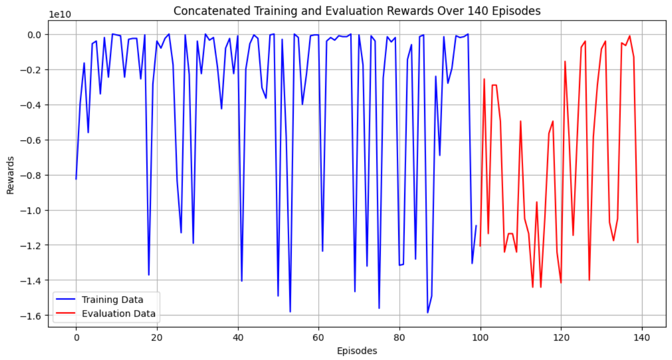
Input

Result

Scenario 1.1 Day patterns

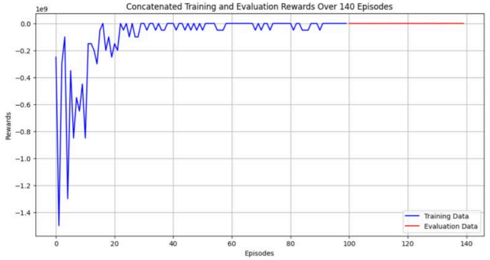


Scenario 1.2 Week patterns

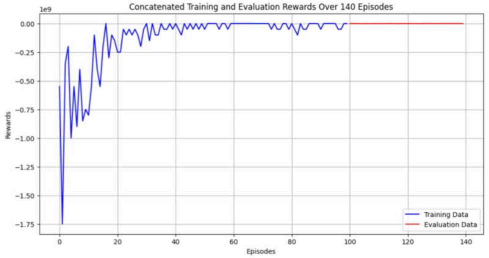


Results Scenario 2 – Less demand

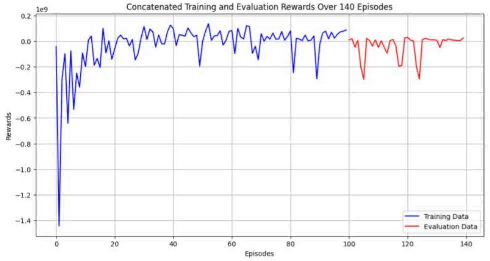
Decreased loads with factors 0.8 until 0.2



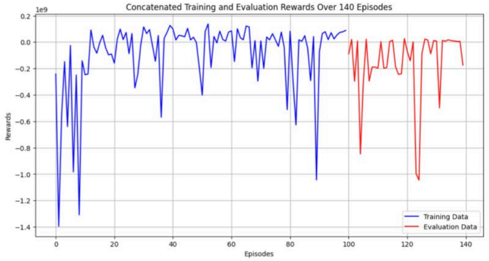
(a) Training curve for environment with base parameters and the loads with a factor 0.2



(b) Training curve for environment with base parameters and the loads with a factor 0.4



(c) Training curve for environment with base parameters and the loads with a factor 0.6



(d) Training curve for environment with base parameters and the loads with a factor 0.8

Figure 6.4: Scenario 2: Concatenated training and evaluation curves

Table 6.4: Summarized version of: Evaluation rewards for sub-scenarios within scenario 2, see Table F.3

Episode	Base case	Scenario 2.1	Scenario 2.2	Scenario 2.3	Scenario 2.4
1	-401440312.5	-263850.225	-562632.52	11243708.78	-88906300
..	..	..	..	..	..
40	-1701428874	-287048.409	-606910.991	25922762.41	-174252802.5
Average	-9.31E+08	-2.46E+05	-5.25E+05	-3.47E+07	-1.59E+08

Results

Findings coming forward in the (sub)scenarios

Scenario 1

Base case

- Tested daily and weekly patterns
- For both runs no optimal learning, or convergence
- **Daily patterns:** Higher rewards, less variability and more stable learning

Scenario 2

Demand side decrease

Loads 0.8, 0.6, …

- Behavior as expected
- **High variability everywhere →** stochastic data selection
- Higher demand is **more complexity**

Scenario 3

Increase in RE supply

Solar Energy only

- No convergence

Solar Energy increase

- Improvement in reward but not in variability

Heat pump

- Improvement in reward and in variability

Scenario 4

Increase (EV) battery storage

More Battery (Speed)

- Not as expected, but understandable
- No improvement, due to more complexity
- Lack of more comprehensive states

EV Batteries (18pm – 7am)

- No convergence

Hybrid scenario

The most desired balanced combination of components

Scenario 5.5.Longer

Longer Training & Evaluation

- 400 training episodes and 200 evaluation episodes

Scenario 5.5.Seasonal

Seasonal data split

- 2,5 months training and 0,5 month evaluation every season

Scenario 5.5.Optuna

Hyperparameter tuning with Optuna

- learning_rate, 2.02e-05,
- gamma 0.93
- epsilon_decay: 0.93

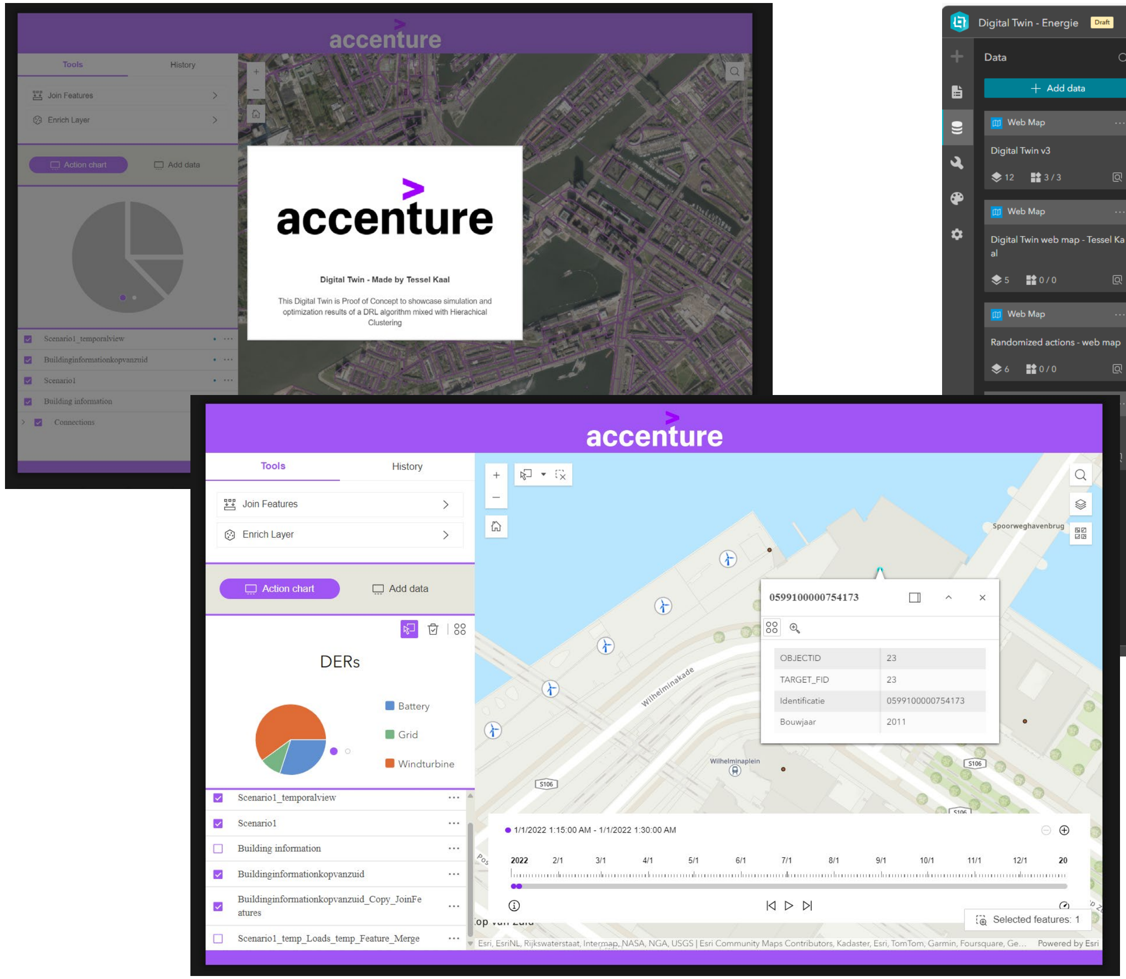
Results: Digital Twin

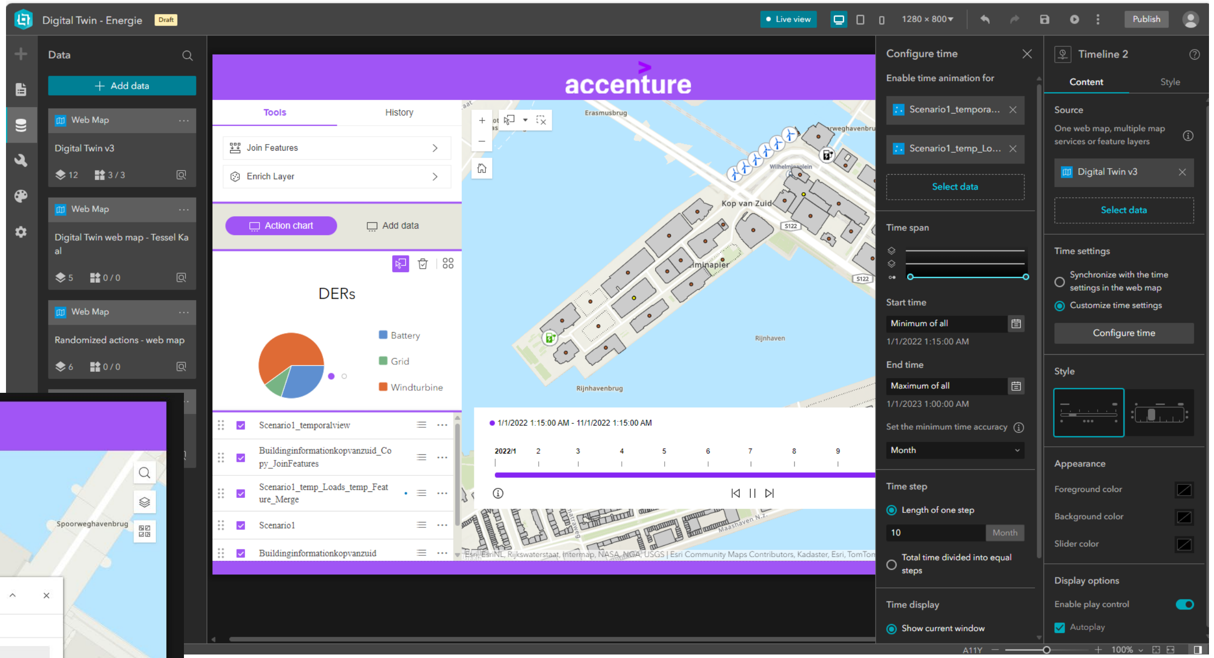
Digital Twin: ArcGIS

Visualization of the work which functions as showcasing method

Digital Twin: Experience Builder

Visualization of the work which functions as showcasing method



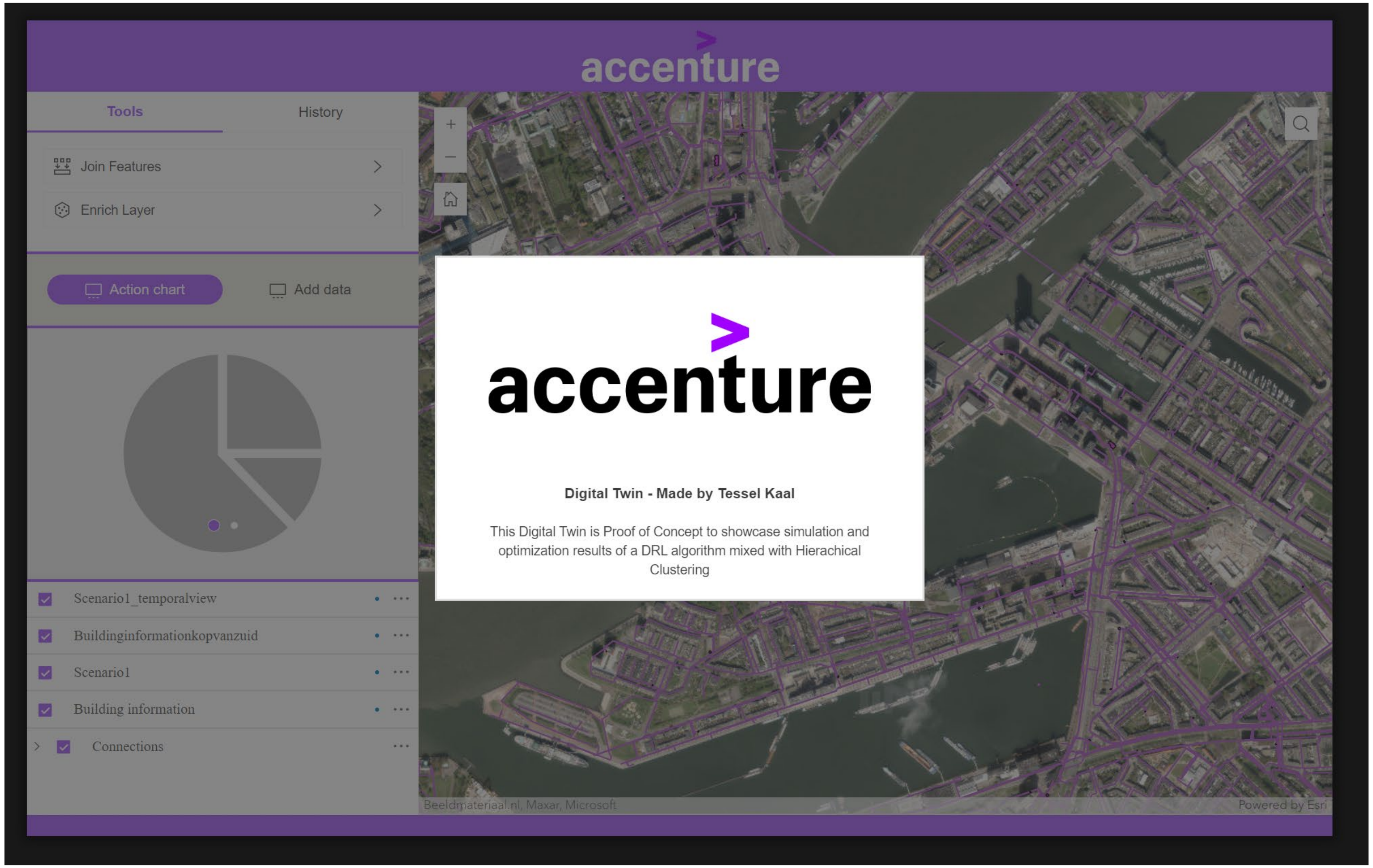


Digital Twin

Visualization of the work which functions as showcasing method

- Proof of Concept showcased internally in ArcGIS experience builder

- Hosted as map layer on Arcgis Online (AGOL)



Conclusion

Conclusion

Answering the research question

Research question:

How can Distributed Energy Resources be deployed and managed, in a cost-effective manner, within an electrified microgrid to achieve a balance between energy consumption and production in order to minimize the burden on the central grid given fluctuating demand?

Conclusion

Answering the research question

- Deployment and managing of the MEM, with:
  - Scalable simulation techniques using open Geographical data
  - Deep Reinforcement Learning model for variable scenarios
  - Dynamic mappings and visualization

- The pipeline facilitates set up and testing of Microgrid scenarios for urban environment in the Netherlands
  - A practical solution

- A Digital Twin with a modular and standardized set up can provide stakeholder with insights

Recommendations

Recommendations

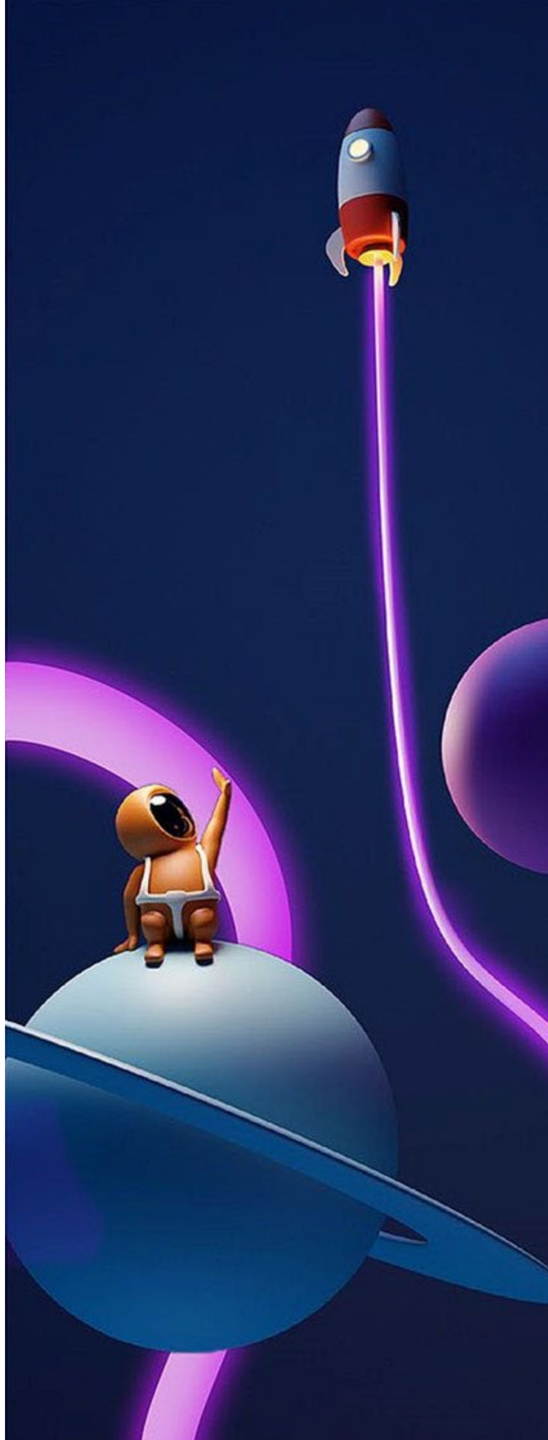
What would be suggested for further work

- Extend model further by
  - More realistic models, like:
    - Comprehensive battery charging and discharging models
    - Use wind turbine models for the wind speed and generation or solar roof analysis
    - Model EVs and charging stations with greater detail
  - Adding and comparing multiple algorithms

- Extend Pymgrid with more modules
  - A redefined action space

- Extensive testing overall to avoid loss in confidence and risks of failure

- Novel approach integrating GNN and clustering can address the varying topologies and non-uniformity of energy microgrids, to balance on more local level and minimize over distance/routing



Thank You

Appendix

Proposed novel approach: GNN and dynamic clustering

DQN brings limitations with a quickly growing action space

- Distances and routing optimization enlarge the action space until not feasible computation time
- Almasan et al. (2022) implement DRL + Graph Neural Network for internet routing optimization:
  - Deep Reinforcement Learning meets Graph Neural Networks: exploring a routing optimization use case
  - Creating a generalized agent for all topologies
- Results show great performance on unknown topologies for structures up to 100 nodes
- Agent is able to traverse unknown sub-micrograids
  - To investigate:
    - Time interval for dynamic clustering

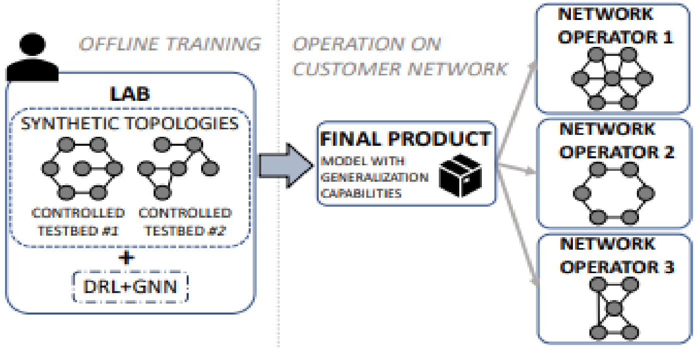
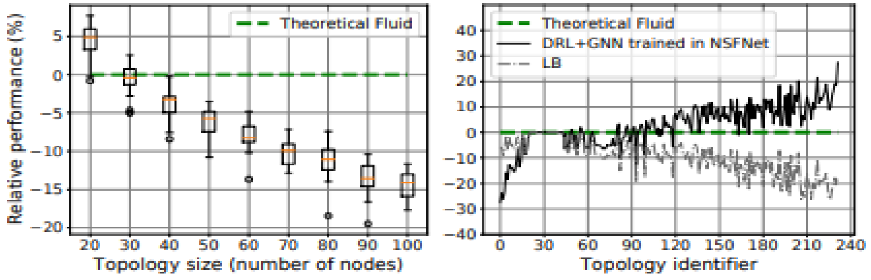


Fig. 7: DRL+GNN deployment process overview by incorporating it into a product.



(a) (b)

Fig. 8: DRL+GNN relative performance with respect to the fluid model over 180 synthetic topologies (a) and 232 real-world topologies (b).

(Sub) Research questions

How can Distributed Energy Resources (DERs) be deployed and managed, in a cost-effective manner, within an electrified microgrid to achieve equilibrium between energy consumption and production, in order to minimize the burden on the central grid given fluctuating demand?

1. Modelling aspects: MG & EMS

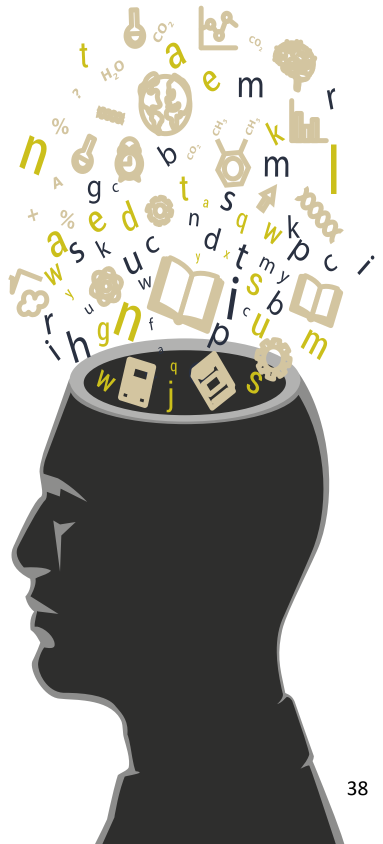
Which modeling aspects need to be considered when designing a microgrid and its energy management system, and how are these reflected in the existing literature?

2. RL implementation

How can reinforcement learning be utilized to effectively place and manage all identified modeling aspects in a microgrid while maintaining grid stability and reliability?

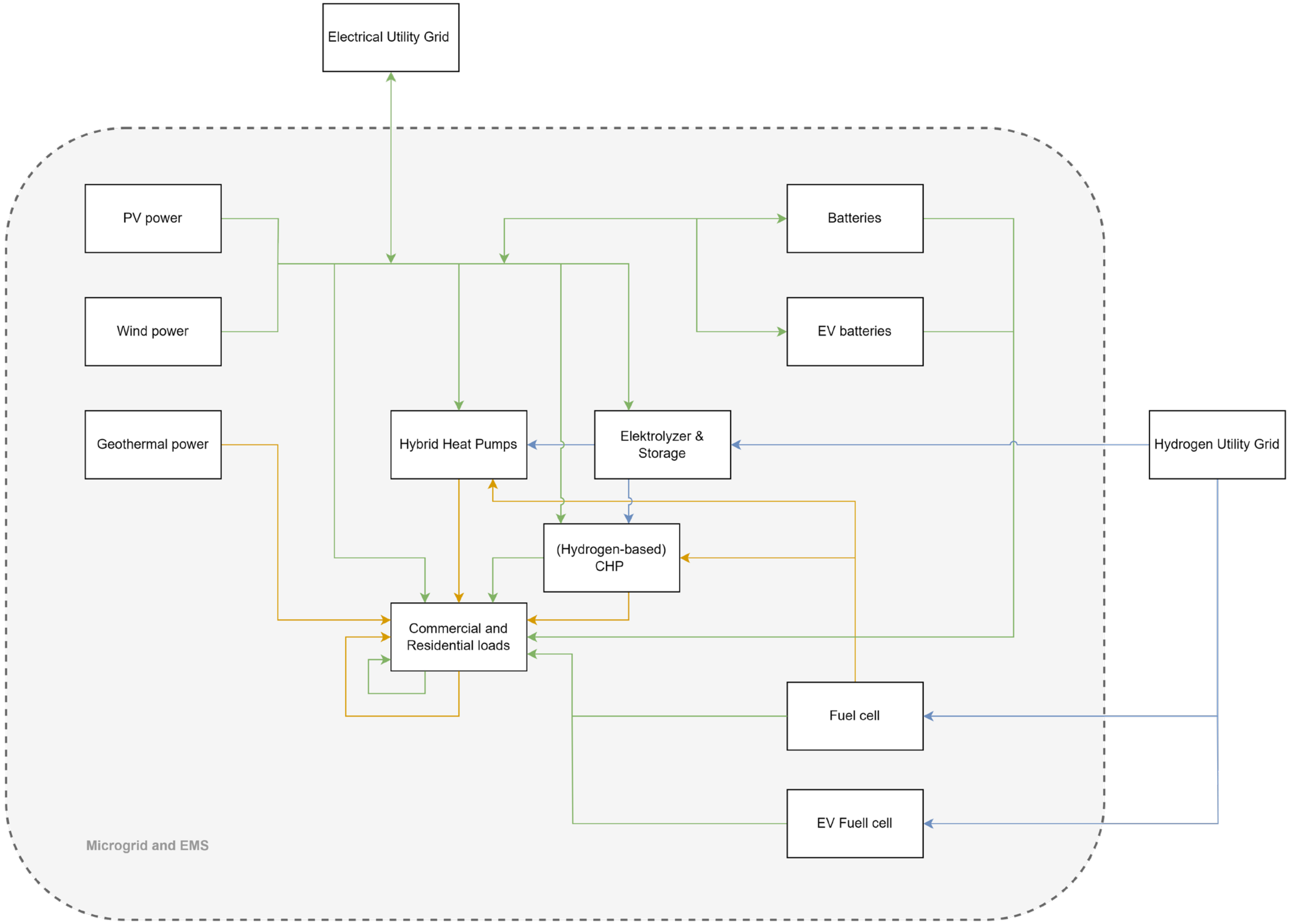
3. Visualization

How can the location-based optimization of a microgrid be effectively visualized to ensure it creates value for all stakeholders?



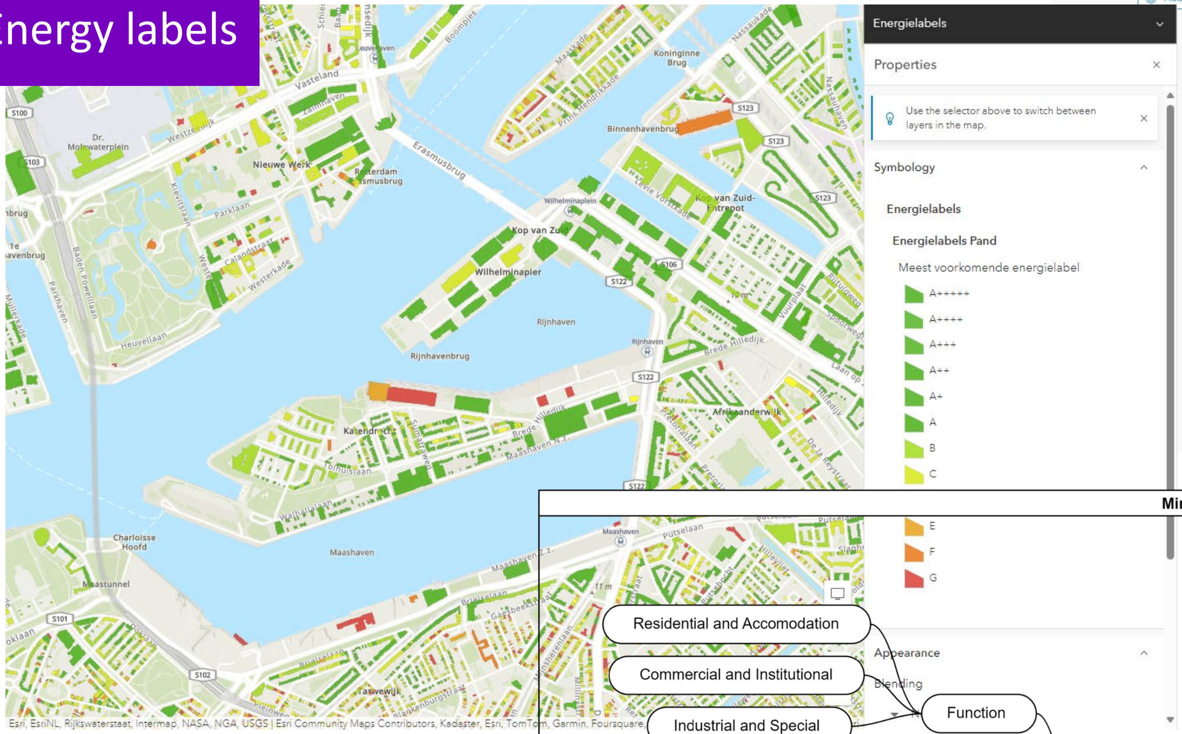
Conceptual Model

Base for scenario composition

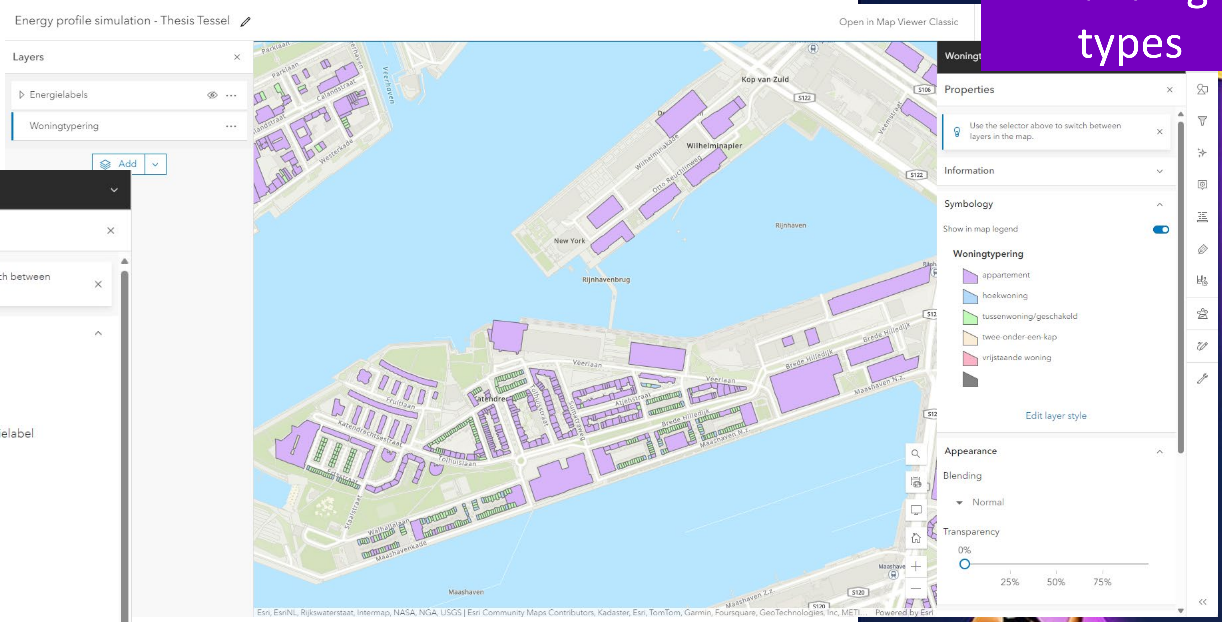


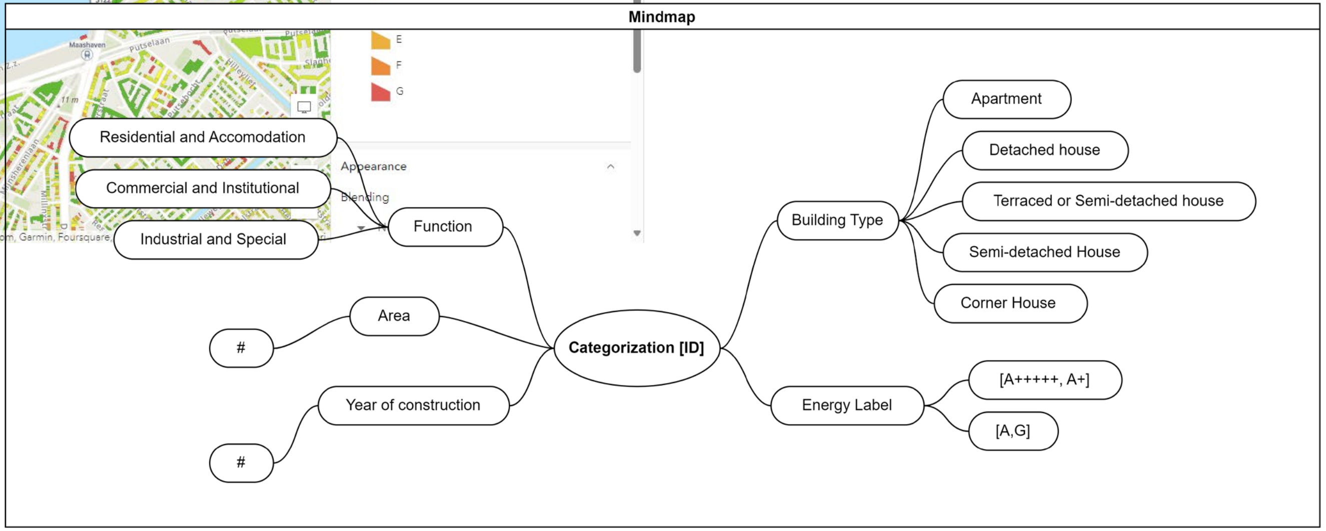
Case study: Fixed environment

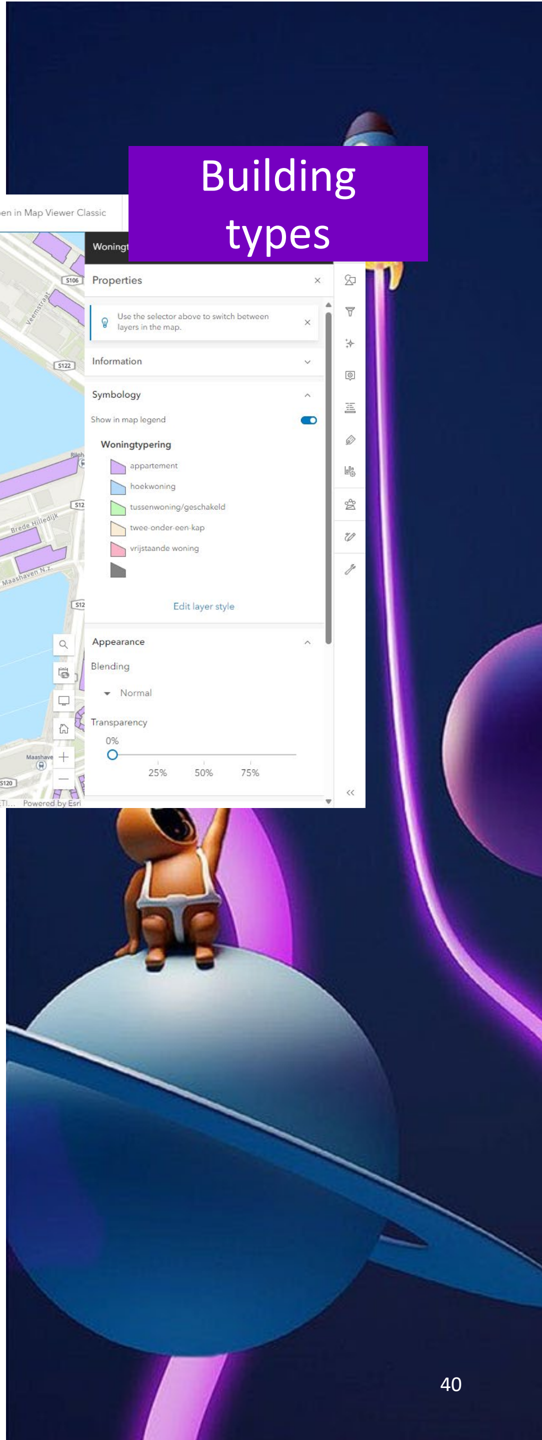
Energy labels



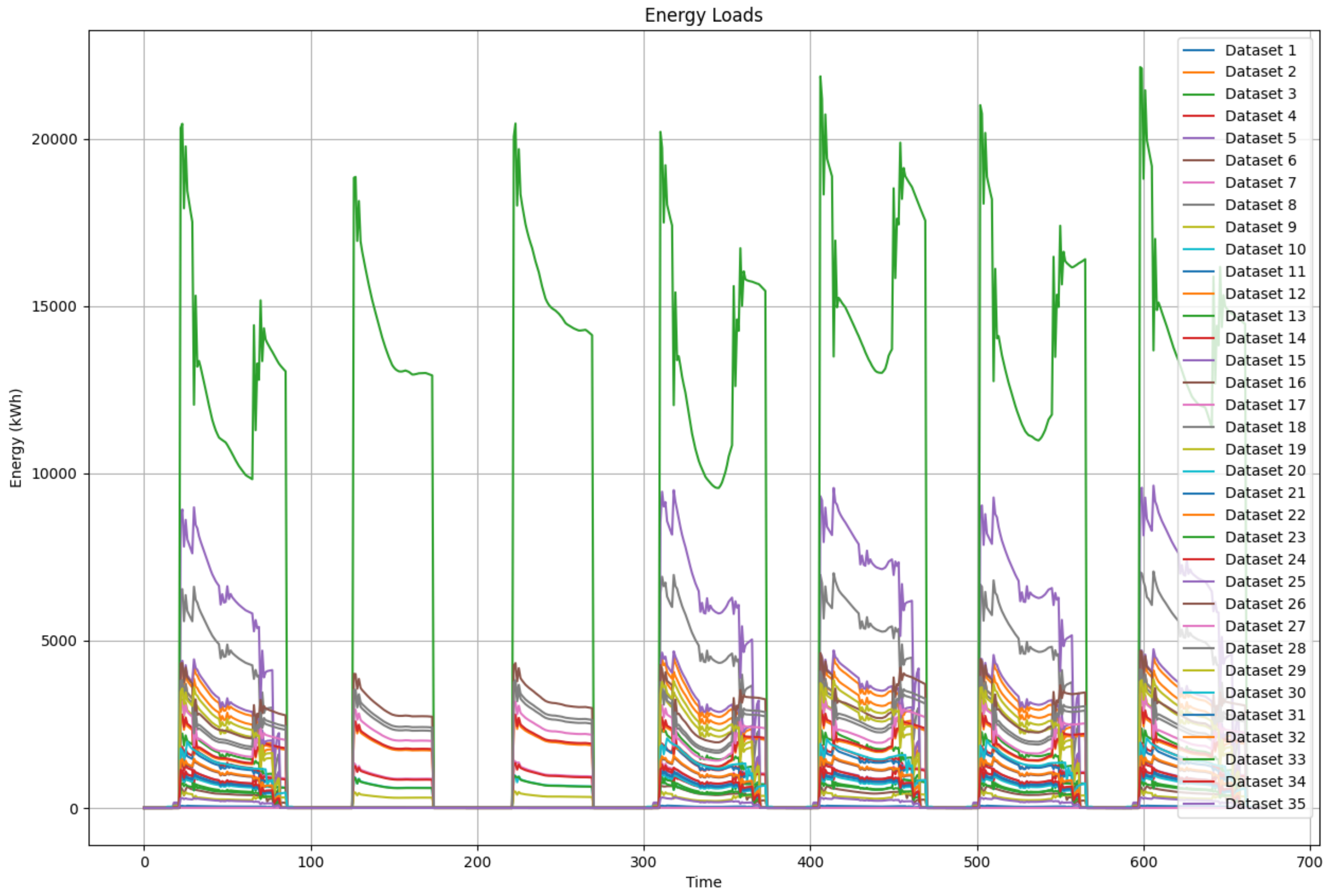
Building types

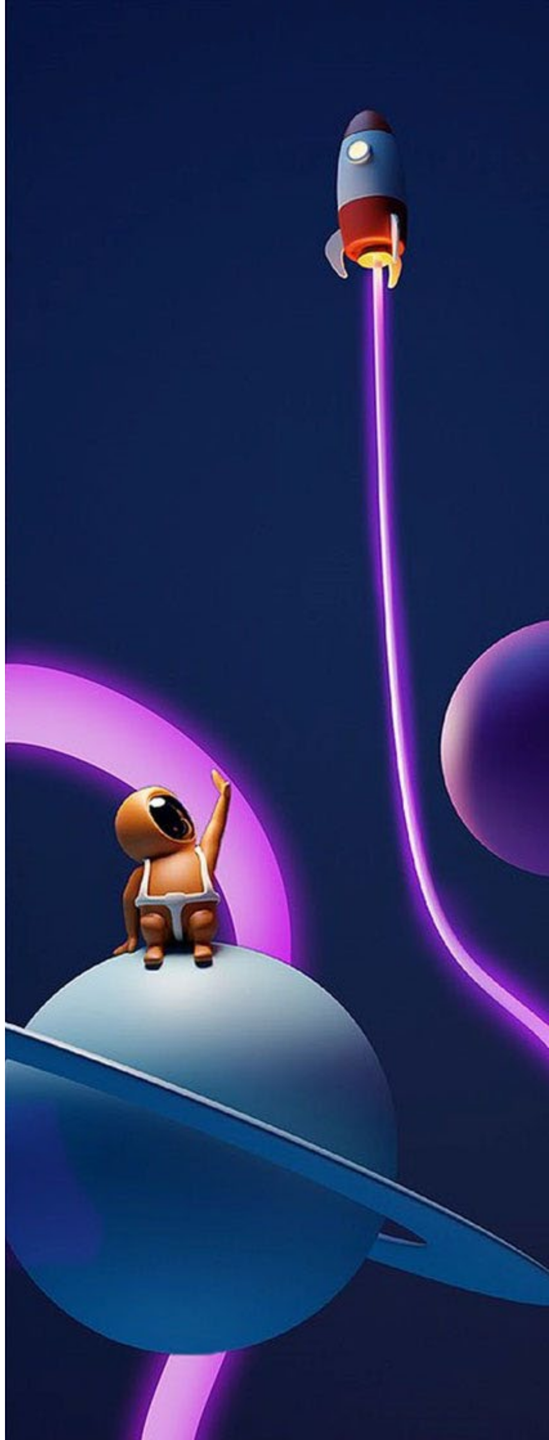






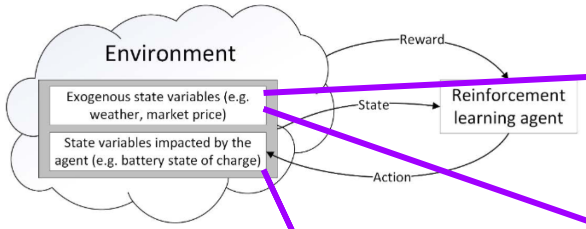
Case study: Fixed environment



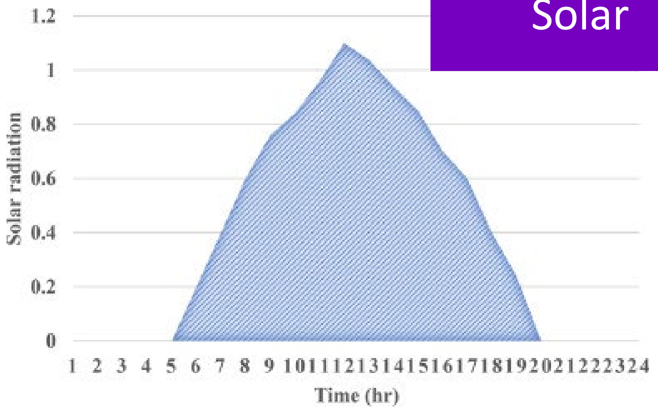


Case study: Variable environment

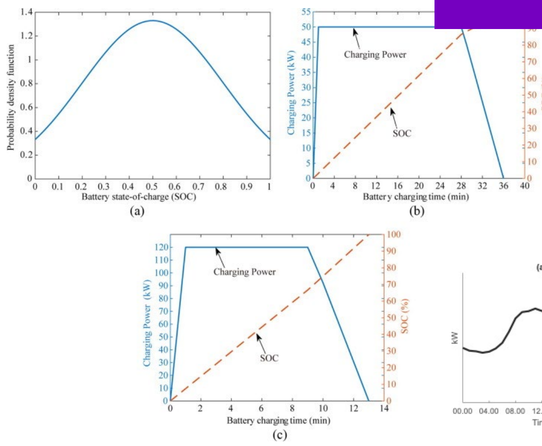
Components and relationships



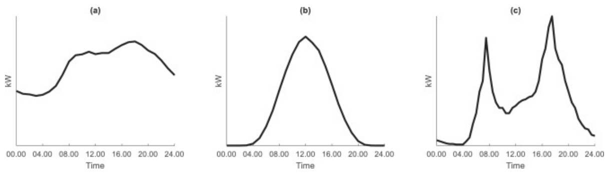
Solar



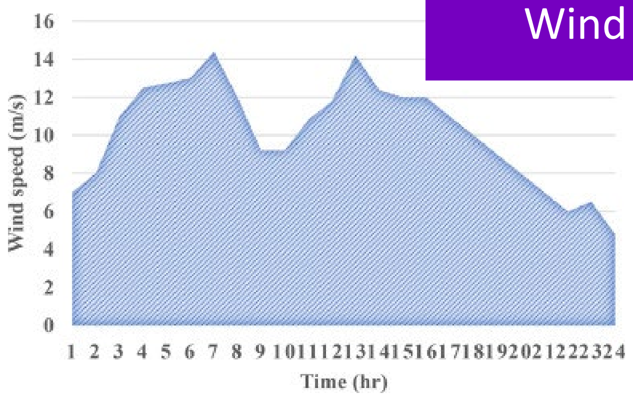
Batteries



Electric vehicles

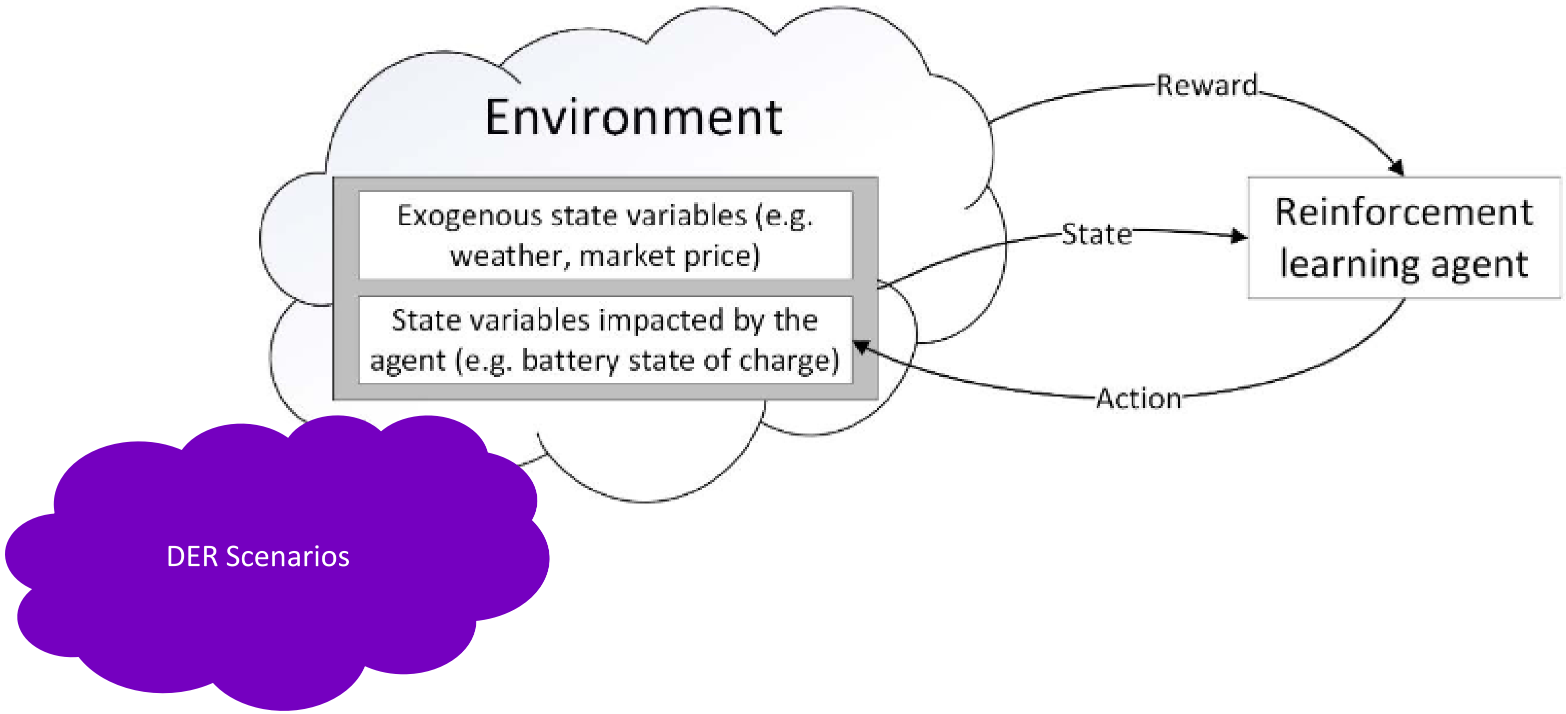


Wind

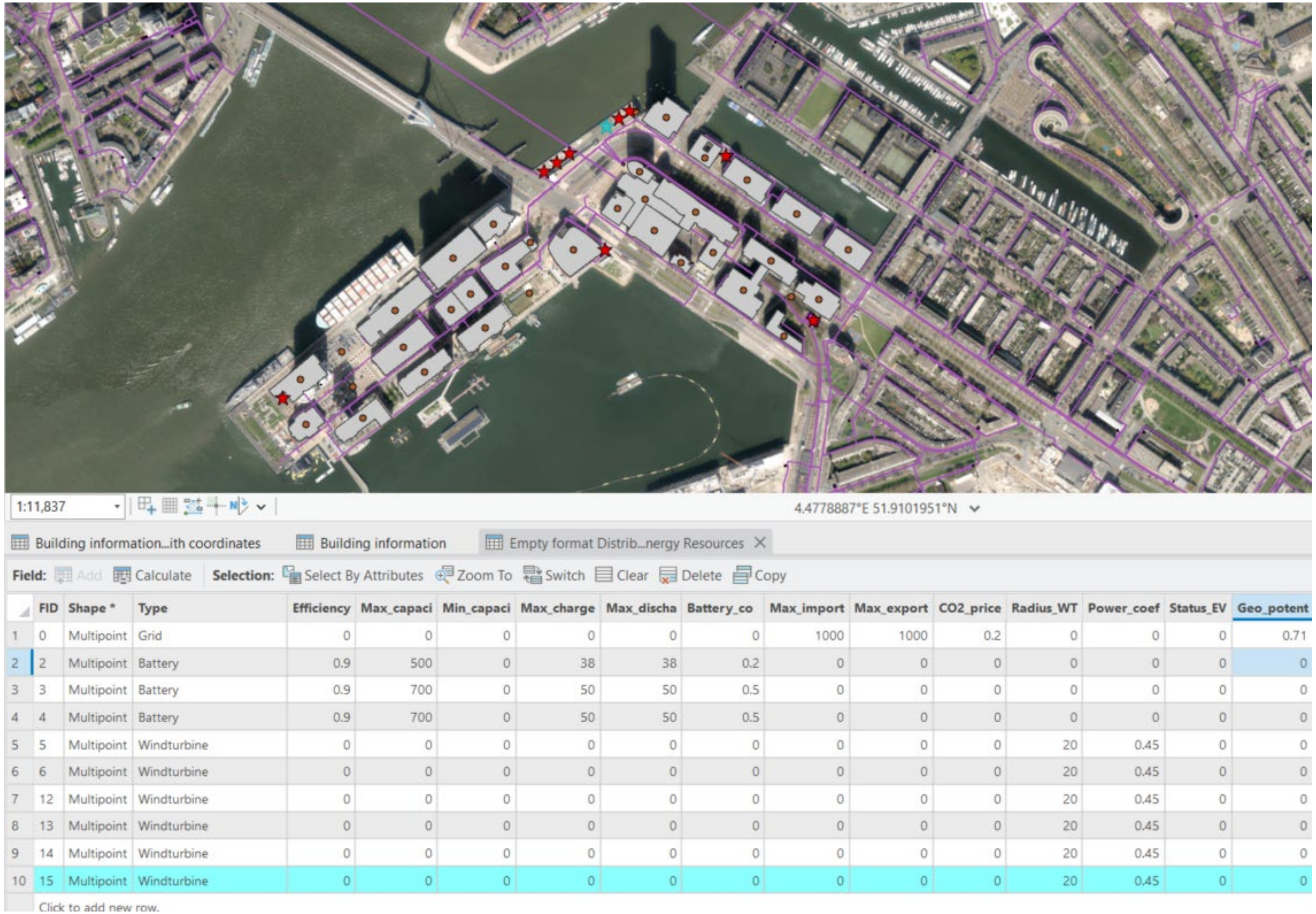


Case study: Variable environment

Components and relationships



Scenario: Basic



	FID	Shape *	Type	Efficiency	Max_capaci	Min_capaci	Max_charge	Max_discha	Battery_co	Max_import	Max_export	CO2_price	Radius_WT	Power_coef	Status_EV	Geo_potent
1	0	Multipoint	Grid	0	0	0	0	0	0	1000	1000	0.2	0	0	0	0.71
2	2	Multipoint	Battery	0.9	500	0	38	38	0.2	0	0	0	0	0	0	0
3	3	Multipoint	Battery	0.9	700	0	50	50	0.5	0	0	0	0	0	0	0
4	4	Multipoint	Battery	0.9	700	0	50	50	0.5	0	0	0	0	0	0	0
5	5	Multipoint	Windturbine	0	0	0	0	0	0	0	0	0	20	0.45	0	0
6	6	Multipoint	Windturbine	0	0	0	0	0	0	0	0	0	20	0.45	0	0
7	12	Multipoint	Windturbine	0	0	0	0	0	0	0	0	0	20	0.45	0	0
8	13	Multipoint	Windturbine	0	0	0	0	0	0	0	0	0	20	0.45	0	0
9	14	Multipoint	Windturbine	0	0	0	0	0	0	0	0	0	20	0.45	0	0
10	15	Multipoint	Windturbine	0	0	0	0	0	0	0	0	0	20	0.45	0	0

Parameter	Variable	Unit
Type	Type	-
Efficiency	$\eta, \eta_{solar}, \eta_{turbine}, E_{geo}$	%
Max_capacity	C_{max}	kWh
Min_capacity	C_{min}	kWh
Max_charge	P_{charge}	kWh
Max_discharge	$P_{discharge}$	kWh
Battery_cost_cycle	$Cost_{cycle}$	Euro
Max_import	Max_import	kWh
Max_export	Max_export	kWh
CO2_price	CO2_price	Euro/KWh
Radius	$R_{turbine}$	Meter
Power_coefficient	C_p	-

DRL+GNN and dynamic clustering

DRL-GNN & Dynamic Clustering

NOW

MG
- Instantiation
- Size of system: loads, batteries, RES, Grid
- Action space: total

Train
- Train agent in complex system
- Complexity asks more training
- Complexity increases required computational effort

Test
- Evaluate and hypertune parameters

DRL-GNN

Train
- Train one agent in one system with a DRL-GNN model

HC
- Use clustering during every timestep
- Create sub microgrids

Test
- Evaluate agents parallel in submicrogrids (constrained)
- Evaluate agent in main microgrid consisting of loads and main grid
- In all sub systems distances can be taken or only in the main system, as HC already limited sub microgrid distance

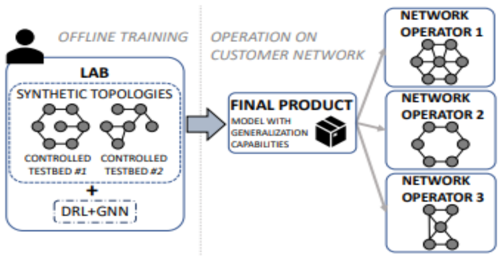
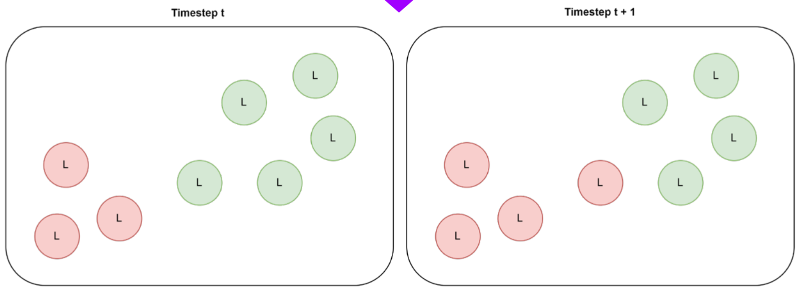
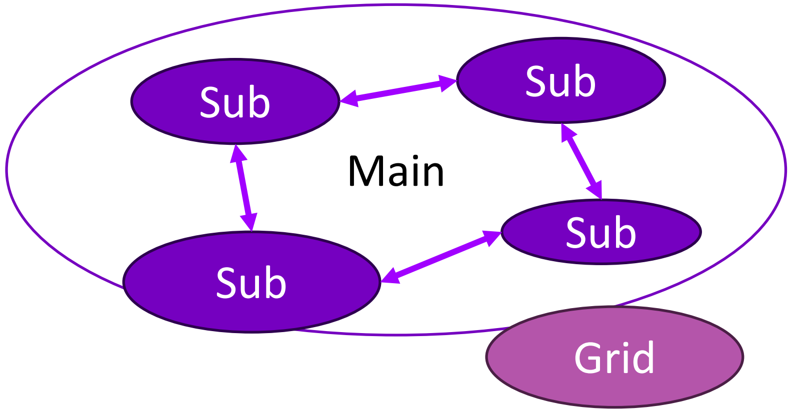


Fig. 7: DRL+GNN deployment process overview by incorporating it into a product.





Future connection for Accenture

Visualization of the work which functions as showcasing method

- Connection with script with ArcGIS and creation of a tool
- Layer connected to (oracle) database
- Interactive running of script

Requirements

- Modularity
  - Format for a scenario
  - Data in uniform formats