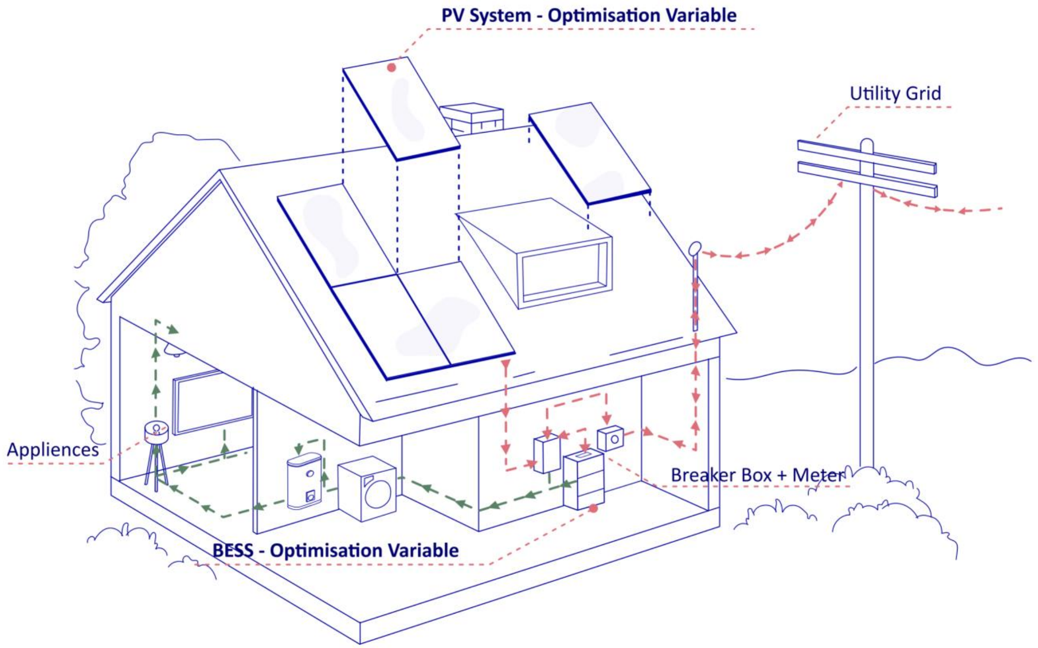
ReinforceRay

Optimal Long-Term Planning of Photovoltaic and Battery Storage Systems for Grid-Connected Residential Sector with Reinforcement Learning



P5 PRESENTATION

04.07.2024

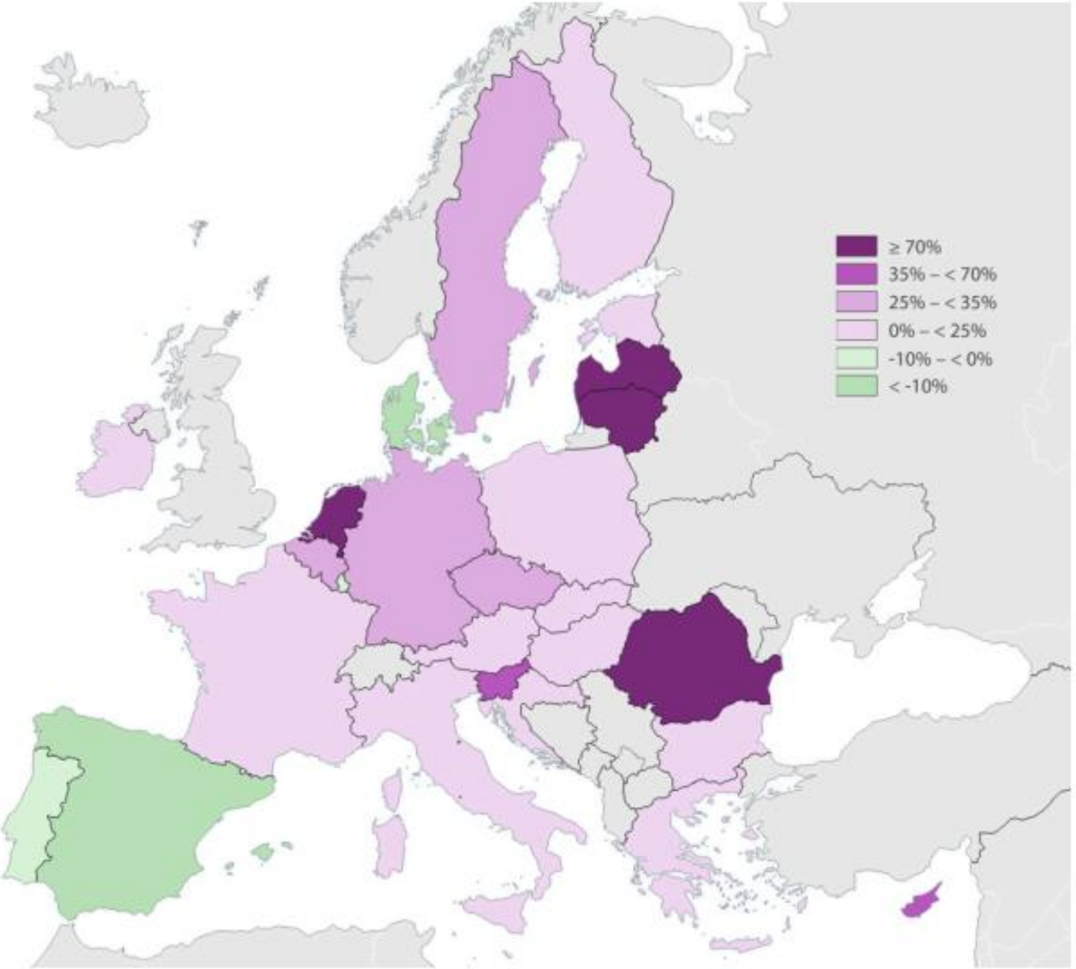
Kuba Wyszomirski

TU Delft

01 Background

01 Background

The last few years have seen a significant increase in energy prices across Europe, initially due to a rebound in energy demand following the relaxation of post-COVID lockdown measures, and subsequently after the Russian invasion of Ukraine.



Change in electricity prices for households consumers, 2022 - 2023

(Eurostat, 2023)

01 Background

Group of European countries aim to decarbonize their electricity system by 2035

News item | 18-12-2023 | 19:45

Today, Austria, Belgium, France, Germany, Luxemburg, The Netherlands and Switzerland announce a joint ambition to decarbonize their interconnected electricity system by 2035, an important step towards a joint path to decarbonize the industrial heart of Europe.

(Ministerie van Economische Zaken en Klimaat, 2023)

Renewable energy targets

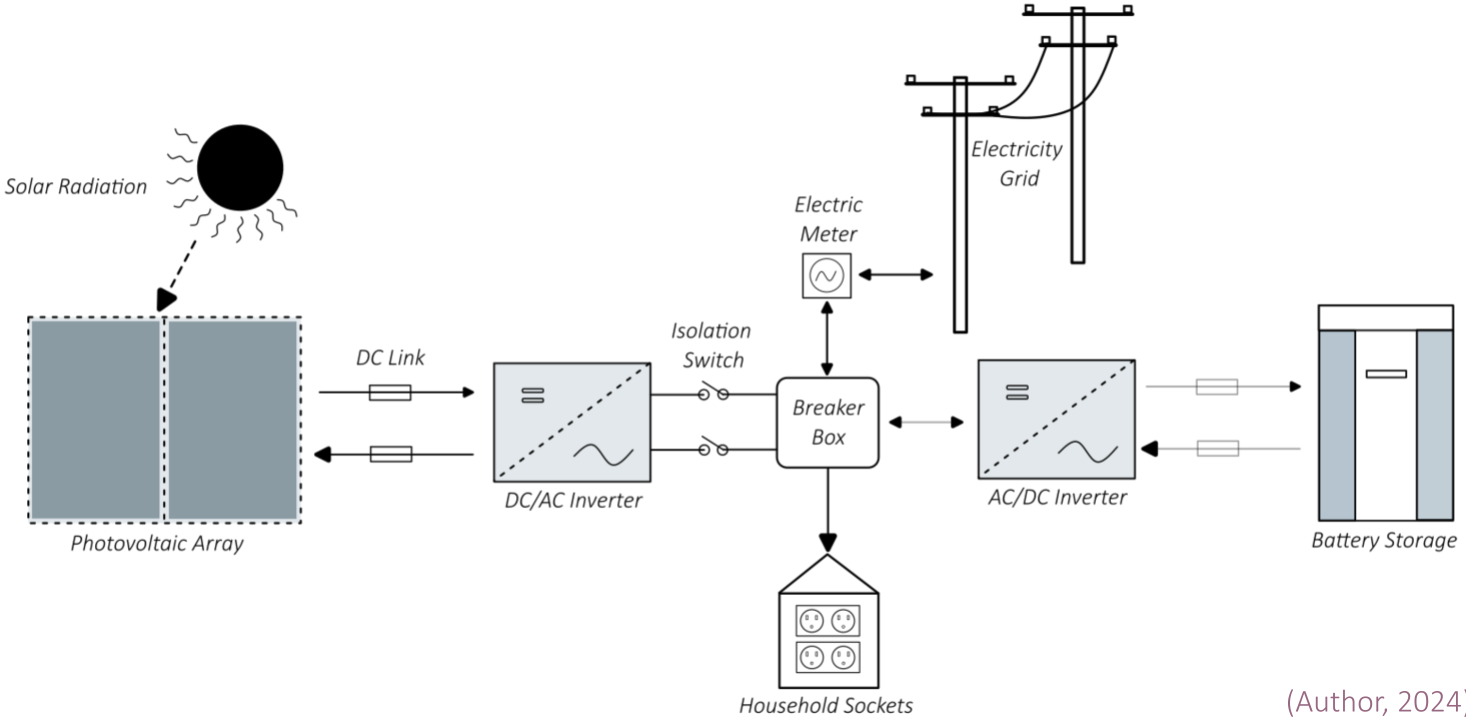
23%	**32%**	**at least 42.5%**
share of renewables in EU energy consumption 2022	2030 target set in 2018	new binding target for 2030, but aiming for 45%

(European Commission, 2023)

As power generation in many European countries still relies on fossil fuels, such as coal and natural gas, the production of electricity leads to the release of large quantities of carbon dioxide into the atmosphere.

01 Background

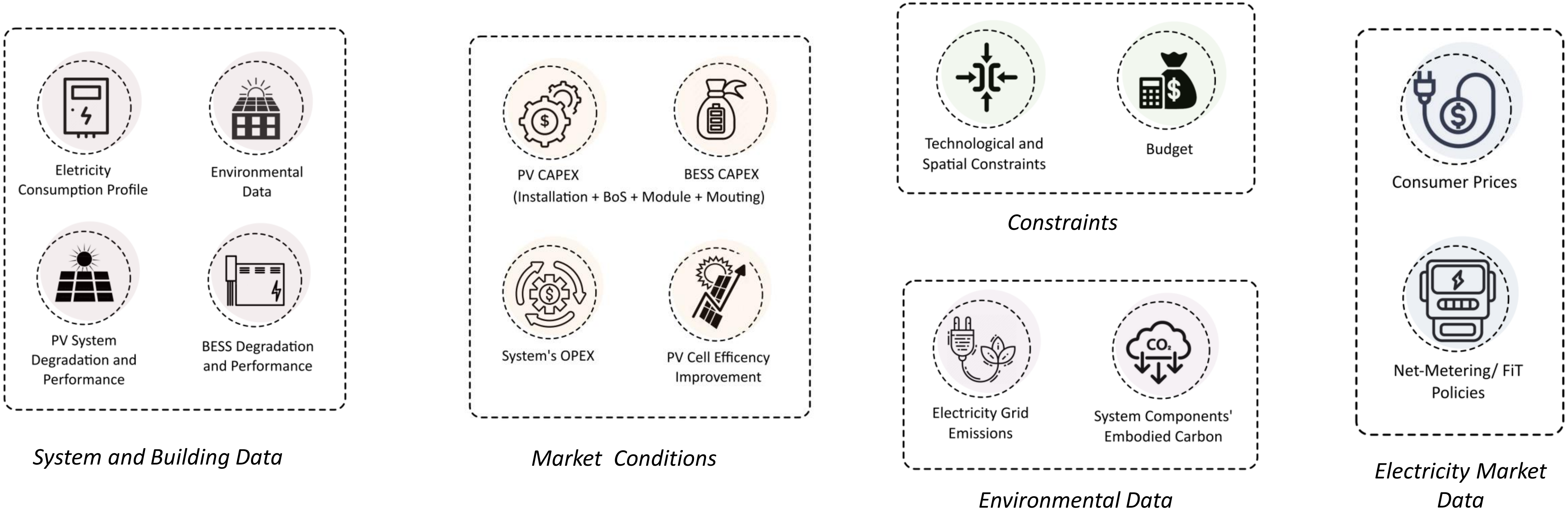
Many homeowners are turning to renewable energy sources. Photovoltaic panels and battery energy storages have become popular solution for generating electricity, reducing reliance on the grid, and even gaining energy independence within the grid-connected residential sector.



(Author, 2024)

01 Background

Yet, estimating the benefits and risks of investing in rooftop PV and BES systems, its type and size, requires is indeed a challenging task requiring consideration of various factors for its adoption and maintenance.



01 Background

Optimal Capacity of PV and BES for Grid-
...stralia

Optimal Sizing of a Solar-Plus-Storage System F...
Utility Bill Savings and Resiliency Benefits

Planning and operatic...
battery systems: A no...

Rajab Khalilpour, Anthony Vassallo

Optimal sizing of residential PV-systems from a household and social cost perspective
A case study in Austria

Michael Hartner[a,*], Dieter Mayr[b], Andrea Kollmann[c], Reinhard Haas[a]

Optimal sizing and energy scheduling of photovoltaic-battery systems under different tariff structures

Orlando Talent, Haiping Du

Optimising the economic viability of grid-connected photovoltaic systems

Jayanta Deb Mondol[a], Yigzaw G Yohanis[a], Brian Norton[b]

Optimal sizing of a nonutility-scale solar power system and its battery storage

Jairo Cervantes, Fred Choobineh*

Optimal Capacity of Solar PV and Battery Storage for Australian Grid-Connected Households

Rahmat Khezri, Student Member, IEEE, Amin Mahmoudi, Senior Member, IEEE, and Mohammed H. Haque, Senior Member, IEEE

Optimal sizing of a residential PV-battery backu...
primary energy source under realistic constrain...

J. Khoury[a,b], R. Mbayed[b], G. Salloum[b,*], E. Monmasson[a]

Optimal design and analysis of grid-connected photovoltaic under different tracking systems using HOMER

Hassan Z. Al Garni[a], Anjali Awasthi[a], Makbul A.M. Ramli[b]

Economic Sizing of a Grid-Connected Photovolta...
System: Case of GISER research project in Morocco

To cite this article: M Khanfara *et al* 2018 *IOP Conf. Ser.: Earth Environ. Sci.* **161** 012006

Battery sizing and rule-based opera...
grid-connected photovoltaic-batter...
system: A case study in Sweden

Yang Zhang[a b], Anders Lundblad[a c], Pietro Elia Campana[c], F. Benavente[a], Jinyue Yan[a c]

...t optimal sizing of smart buildings' energy system components
...sidering changing end-consumer electricity markets

Henryk Wolisz*, Thomas Schütz, Tobias Blanke, Markus Hagenkamp, Markus Kohrn, Mark Wesseling, Dirk Müller

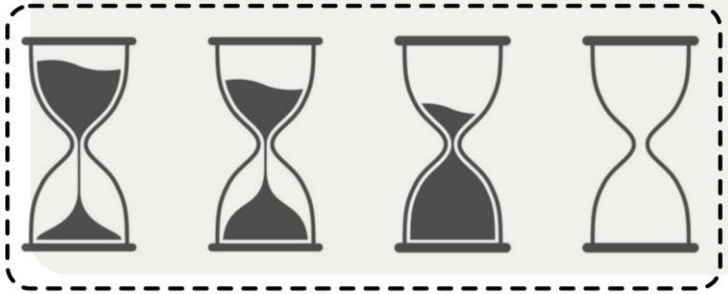
Sizing and grid impact of PV battery systems -
a comparative analysis for Australia and Germany

Contribution for optimal sizing of grid-connected PV-systems using PSO

Aris Kornelakis, Yannis Marinakis

01 Background

TIME!

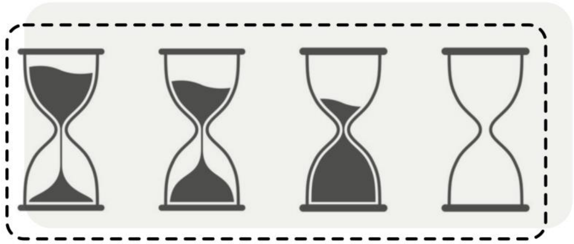


System installation is considered as a one-time now-or-never decision

They are static - do not accommodate modifications to the system throughout its lifetime

Unrealistic assumptions regarding time-dependent variables

01 Background



There is a need for a new risk-mitigating computational optimisation framework what would be able to accommodate for….

Multi-stage strategy with option to expand, replace or contract.

Allow for time flexibility, adapt and update the policy to evolving internal and external conditions.

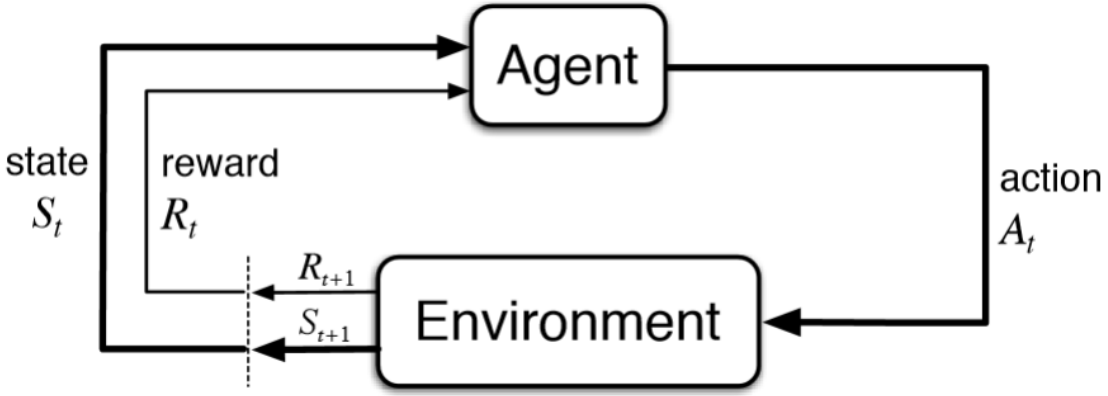
Incorporate a multi-objective scope.

01 Background

All decisions are ultimately informed by data.

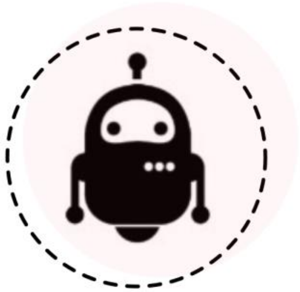
Reinforcement learning *is a paradigm within ML where an agent learns optimal decisions by interacting with an environment through trial and error, making it well-suited for problems where decisions lead to sequences of outcomes over time.*

RL *can handle high-dimensional state spaces and* ***generalize across different scenarios,*** *making itself applicable to complex* ***sequential decision-making*** *tasks.*



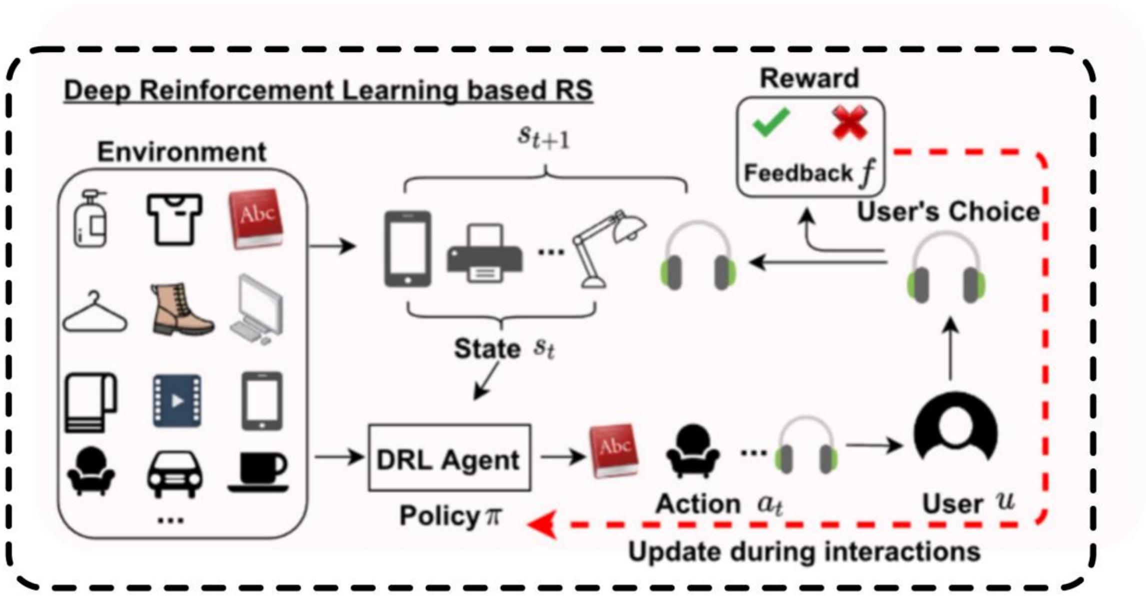
(Sutton & Burto, 2020)

01 Background



Trained Agent

A trained model can be integrated into a ***Recommender System.***

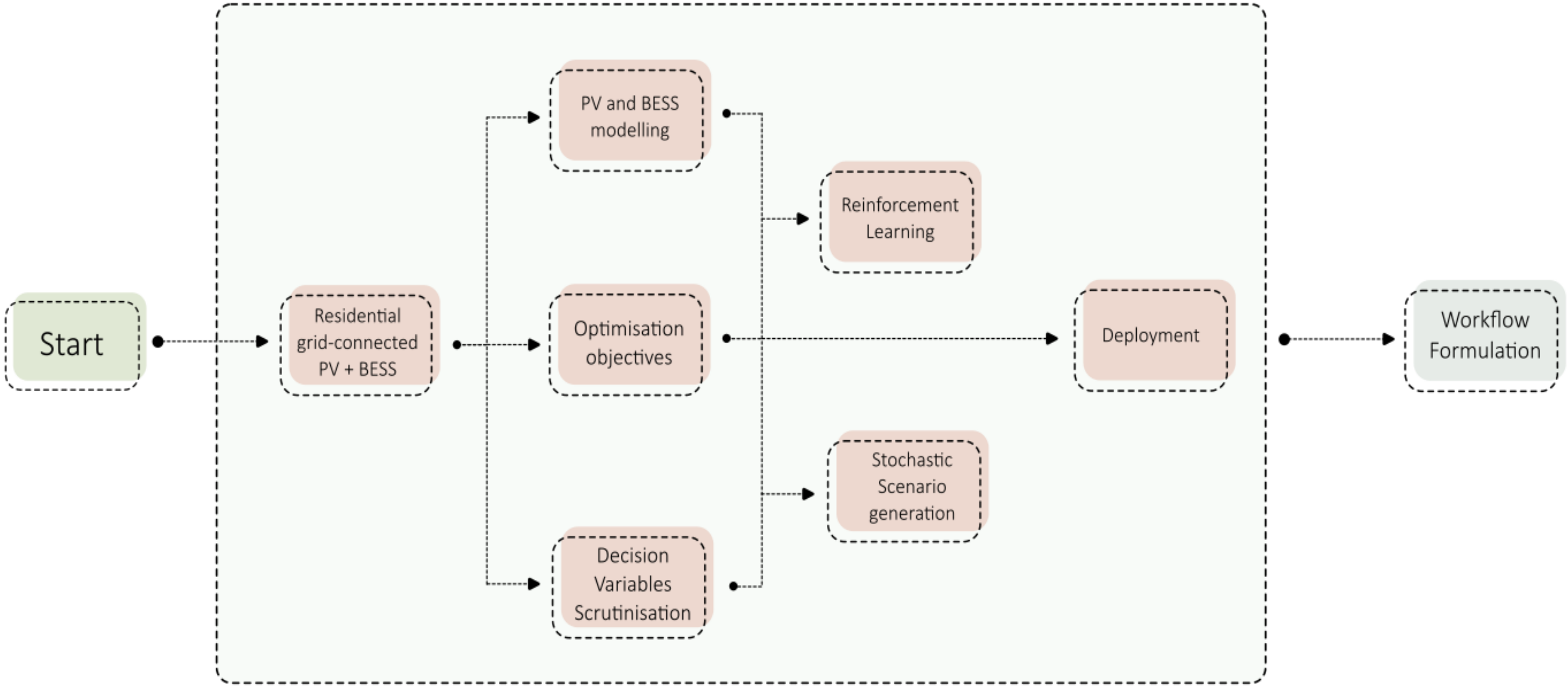


(Chen et al., 2023)

02 Research Question

*How can **reinforcement learning** based **recommendation workflow** be used for long-term planning and design of residential grid-connected **PV and battery storage systems** under the **uncertainty of future scenarios**?*

03 Literature Review



04 Workflow Formulation

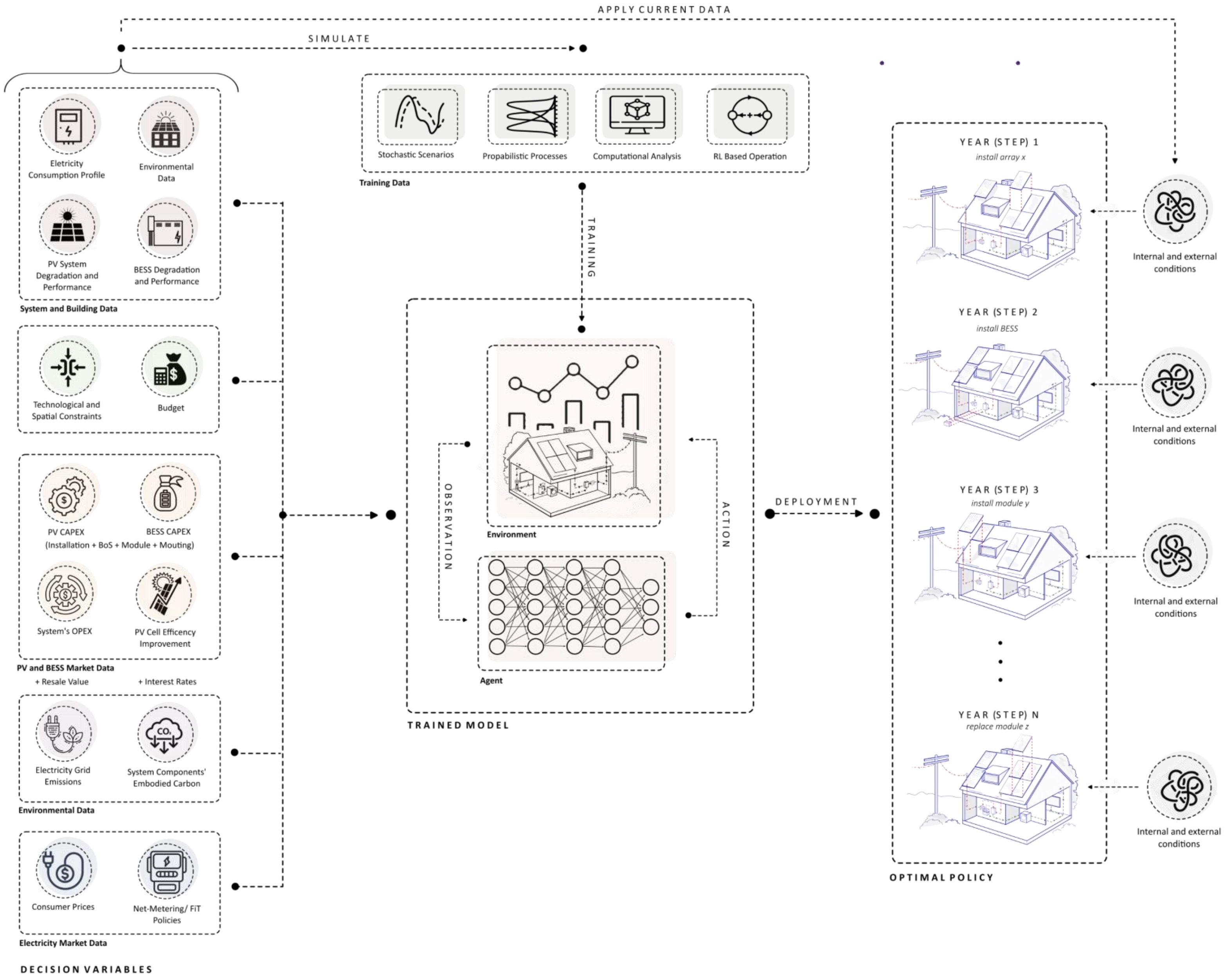
04 Workflow

The problem is structured as a MDP :

- ***Agent*** *recieves observation regarding the current condition of the system, along with current rates of relevant variables*

- *Based on these observations, the* ***agent must execute actions aimed at maximizing the reward****, calculated as the net balance between costs and benefits and/or the net carbon impact.*

- *The optimization process* ***spans 25 years****, divided into equal timesteps.*

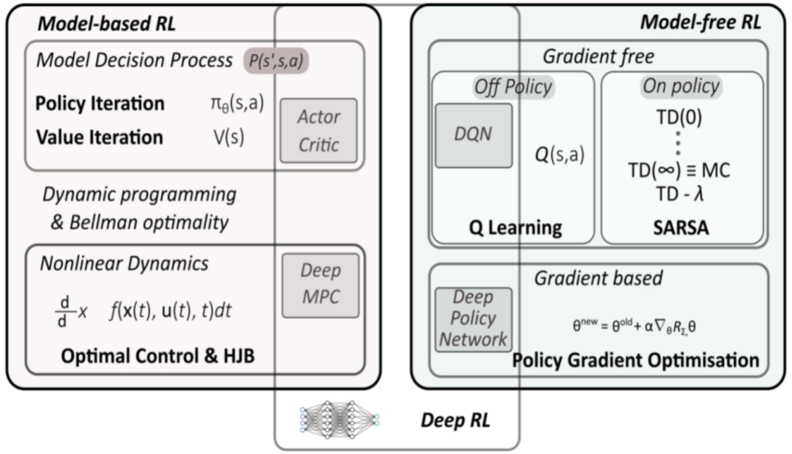


04 Workflow

Criteria:

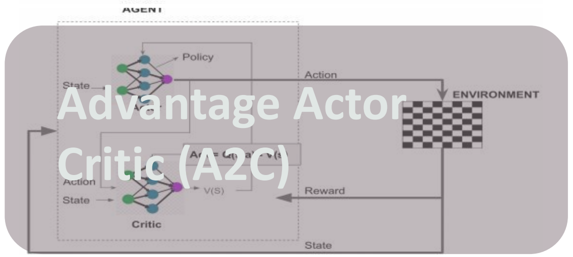
1. *Convergence Speed*
2. ***Robustness and Stability** i.e. its performance consistency across different scenarios*
3. ***Scalability** i.e. handling of increasing complexity*
4. *Multi-Objective Optimization Capability*
5. *Access to learning resources*

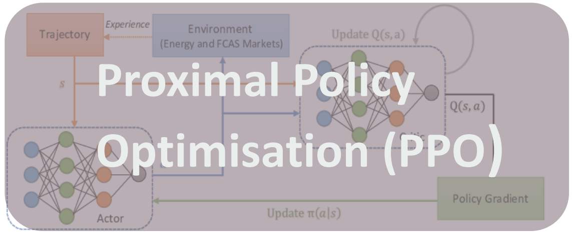
Literature Review and Experimentation:



(Author, 2024)

Selection:



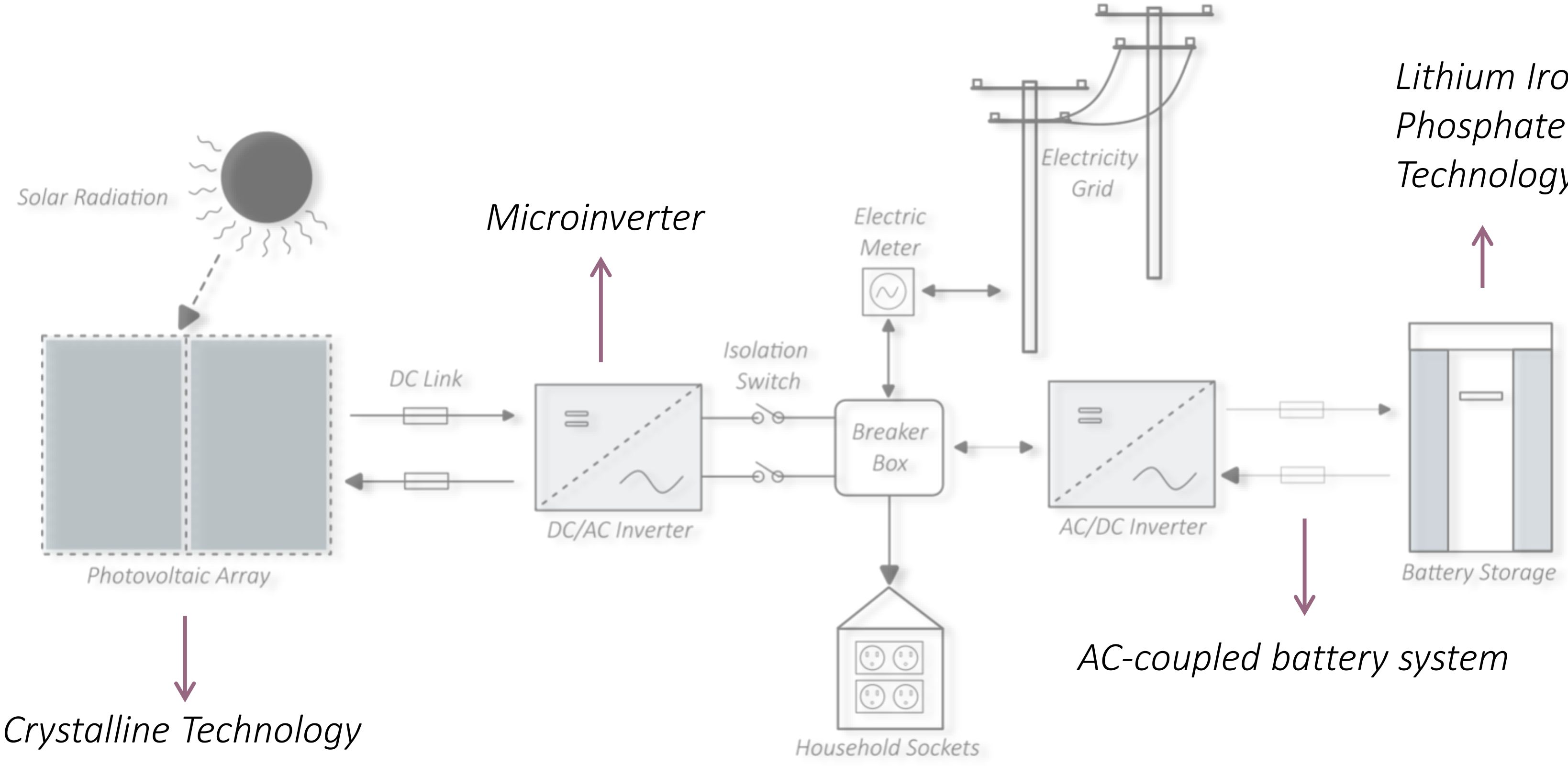


04 Workflow

No outages
No import limit
Export limit at 4kW

Microinverter

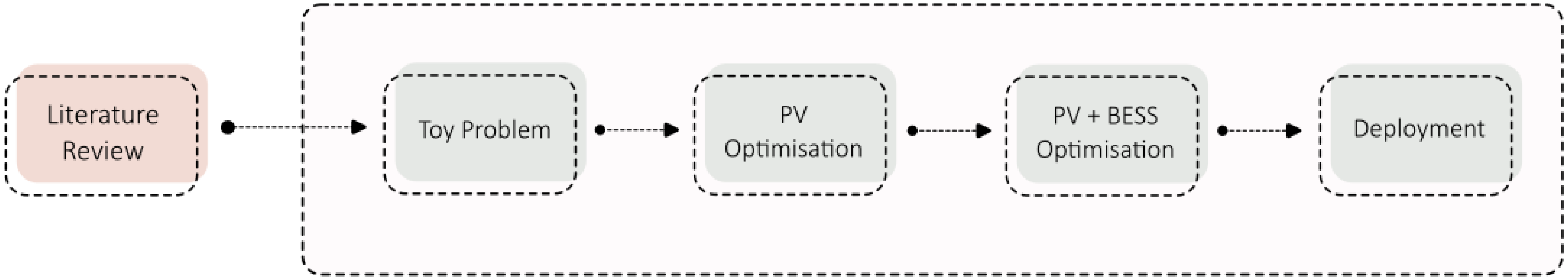
Lithium Iron Phosphate Technology



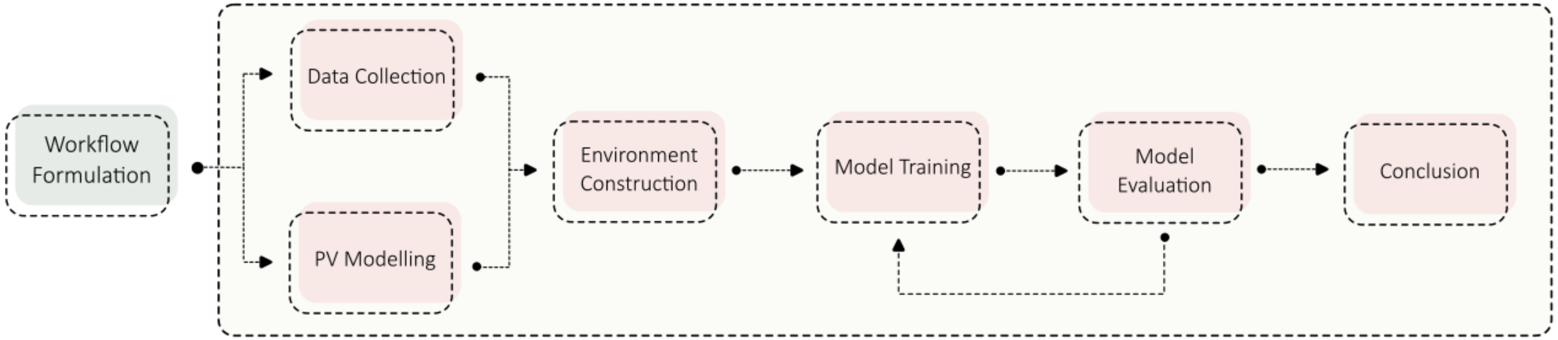
Crystalline Technology

AC-coupled battery system

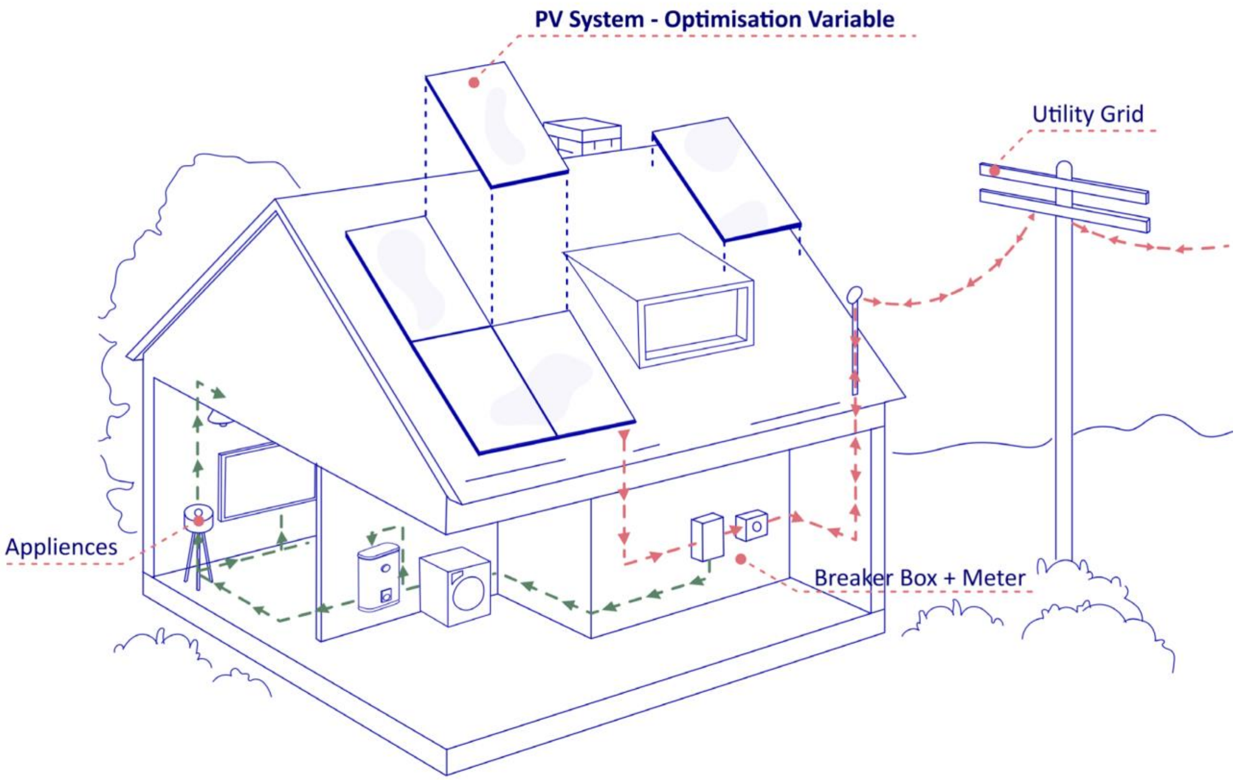
04 Workflow


Literature Review
Toy Problem
PV Optimisation
PV + BESS Optimisation
Deployment

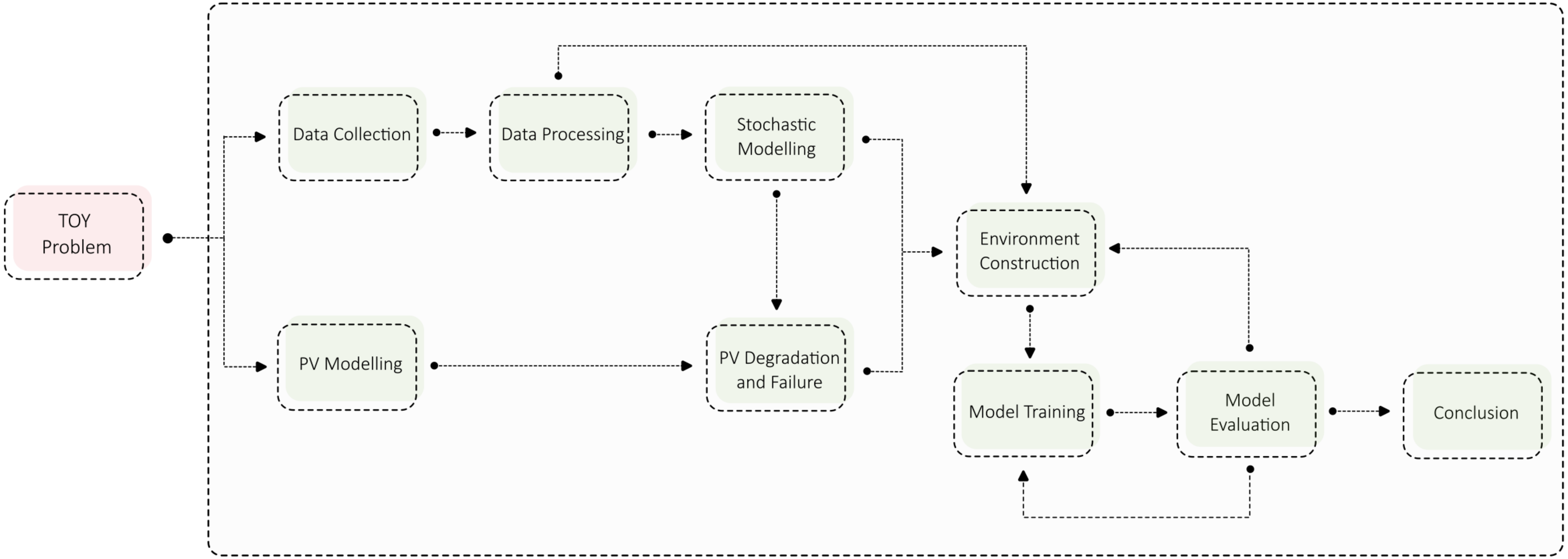
05
TOY Problem



06
PV Optimisation

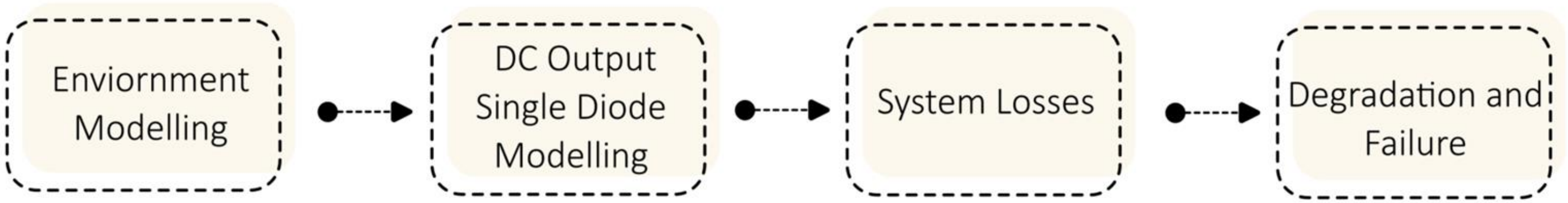


06 PV Optimisation



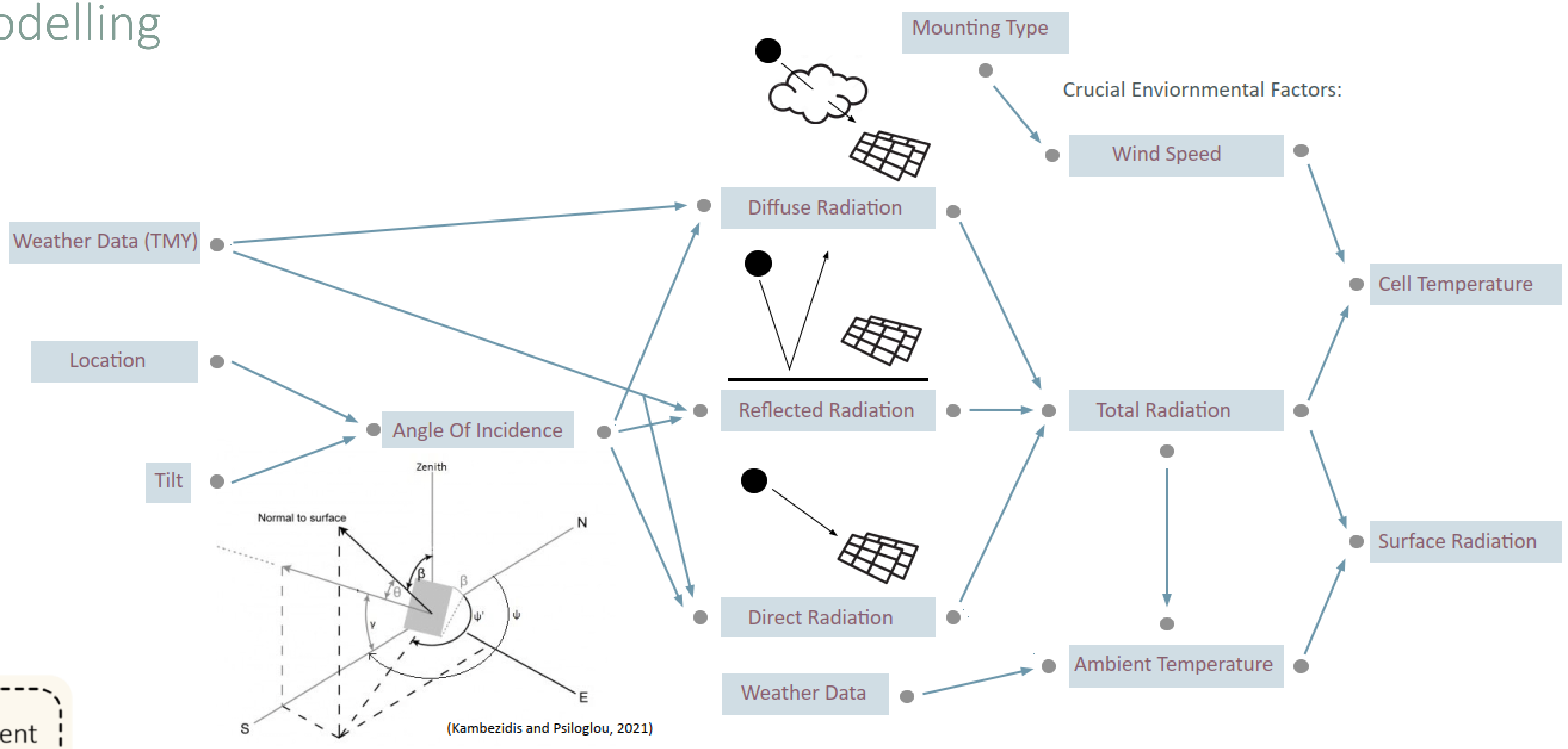
06 PV Optimisation

PV Modelling



06 PV Optimisation

PV Modelling



Enviornment Modelling

06 PV Optimisation

PV Modelling

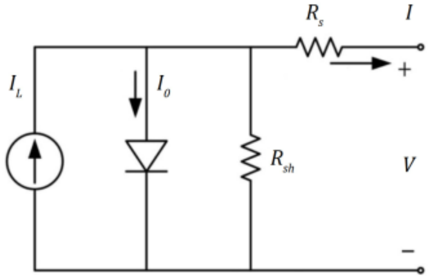
Cell Temperature

Surface Radiation

PV Module Specification

- I_L light-generated current
- I_0 diode saturation current
- R_s series resistance
- R_{sh} hunt resistance
- V_{th} thermal voltage

under Standard Test Conditions

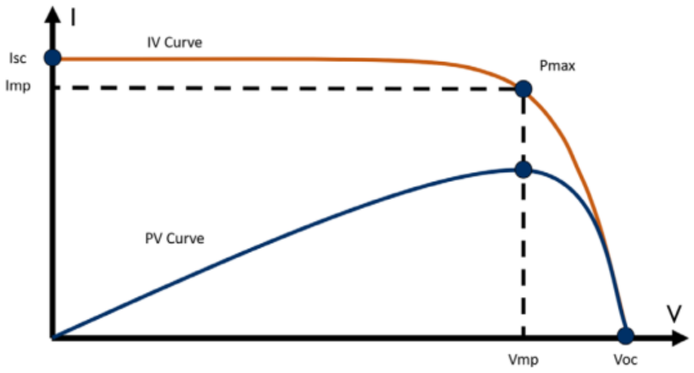


Single Equivalent Circuit (author, 2024)

Current I

$$P_{DC} = I \times V$$

Voltage V

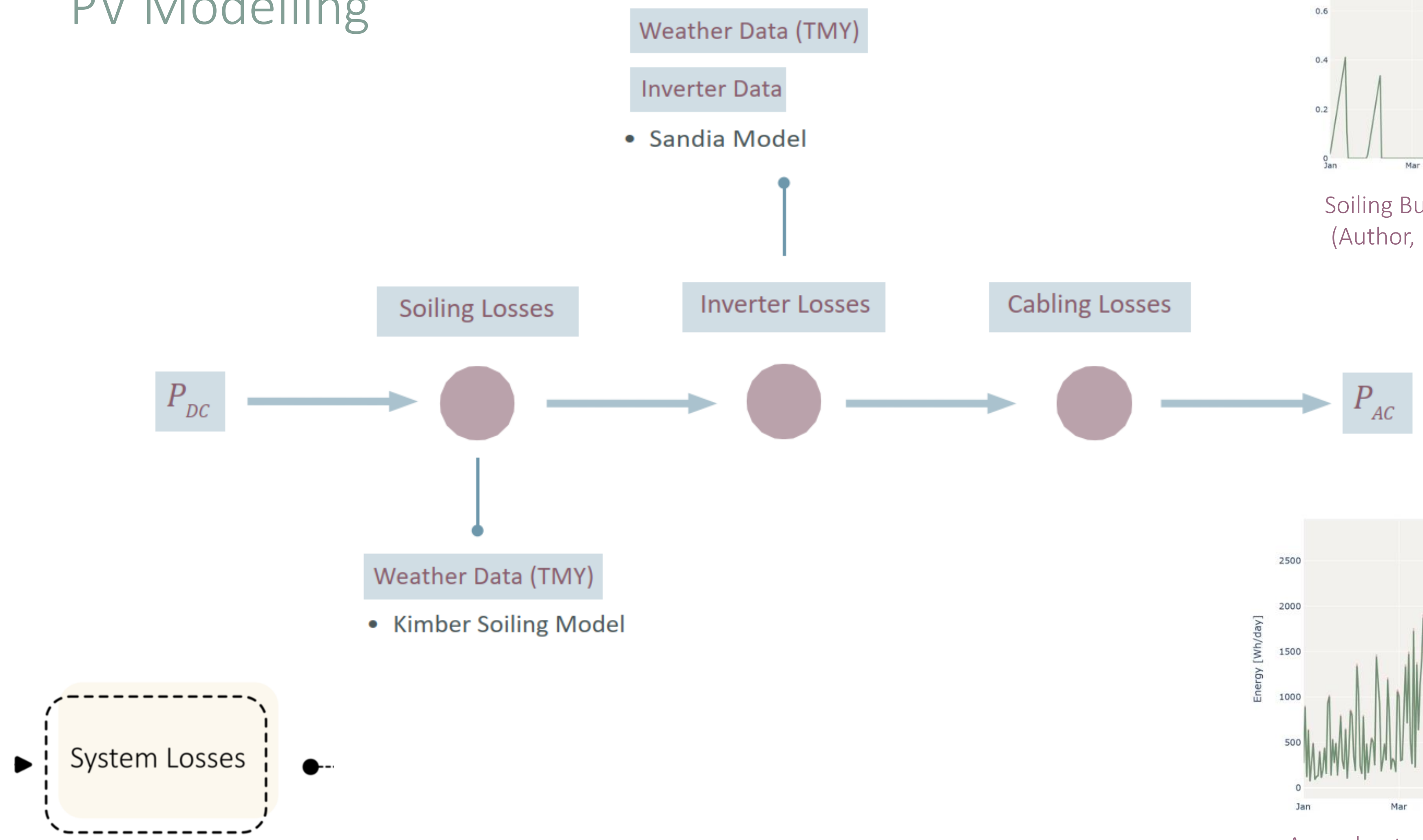


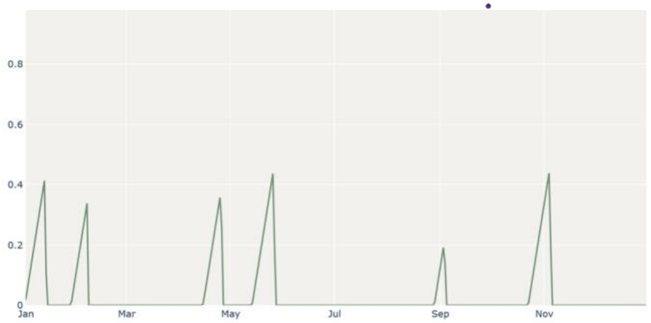
I-V Curve (author, 2024)

DC Output
Single Diode
Modelling

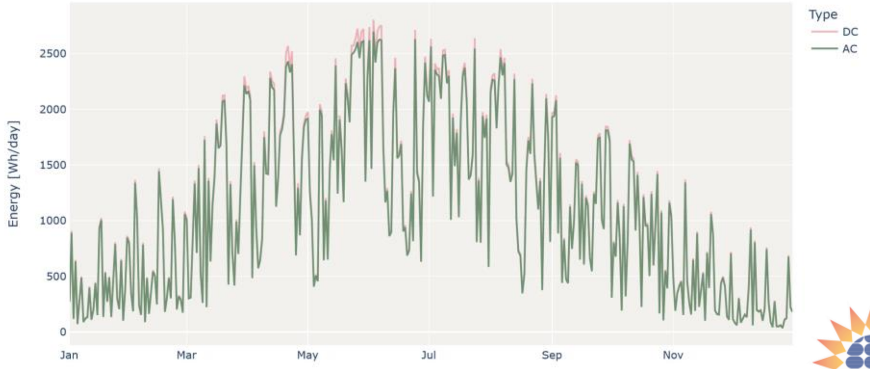
06 PV Optimisation

PV Modelling





Soiling Build-up as % of radiation losses (Author, 2024)



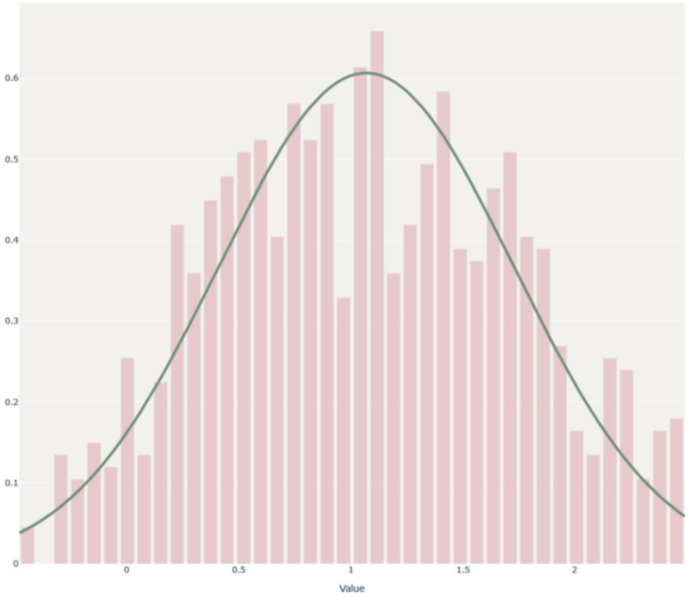
Annual output of a single module (Author, 2024)

pvlib

06 PV Optimisation
Degradation

NREL Degradation Dataset → Data Processing (Square Root) → Distribution Fitting → To environment

→ Degradation and Failure

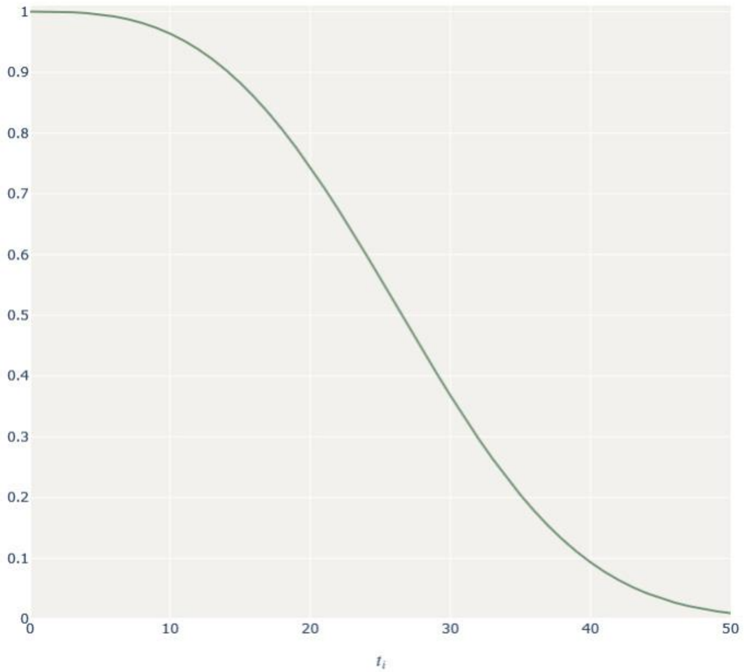


Normal distribution of the annual degradation rate (green), fitted to the data (pink) for the budget panel. (Author, 2024)

$$\eta_i(t) = \eta_i(t-1) - \epsilon_t$$

06 PV Optimisation

Failure



Weibull Distribution for Panel's Survival Rate (Author, 2024)

$$R_{PV,i}(t_i) = e^{-(\frac{t_i}{\varphi})^{\beta}}$$

$$W_{PV,i}(t) = \begin{cases} 1 & if\ \theta_i \leq R_{PV,i}(t_i) \\ 0 & if\ \theta_i > R_{PV,i}(t_i) \end{cases}$$

$$P_{PV}(h) = P_{AC}(h) \times W_{PV,i}(t)$$

Degradation and Failure

06 PV Optimisation

Stochastic Variables Modelling

- Decision variables evolve unpredictably given the inherent volatility influenced by market trends, etc

- Precise long-term price predictions are very challenging

- It is vital to expose RL Model to a wide range of possible scenarios reflecting variables long-term fluctuations.

Stochastic Differential Calculus

$$dX_t = \mu(X_t, t)dt + \sigma(X_t, t)dB_t + dq(X_t, t)$$

Incremental change in the variable at time t.

Drift rate. It models the predictable, average direction in which the system tends to move over time.

Volatility with a Brownian motion quantifies the intensity of the random fluctuations around the drift rate.

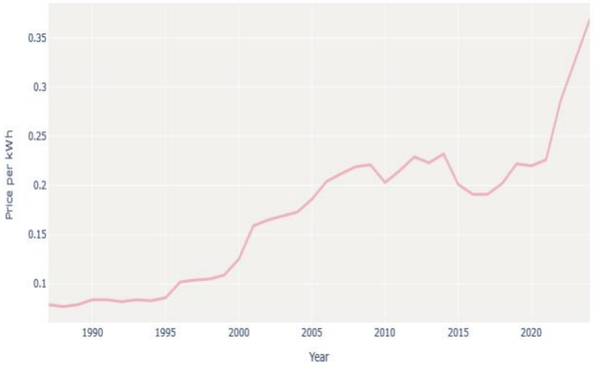
Jump process, capturing sudden and significant changes in the system.

06 PV Optimisation

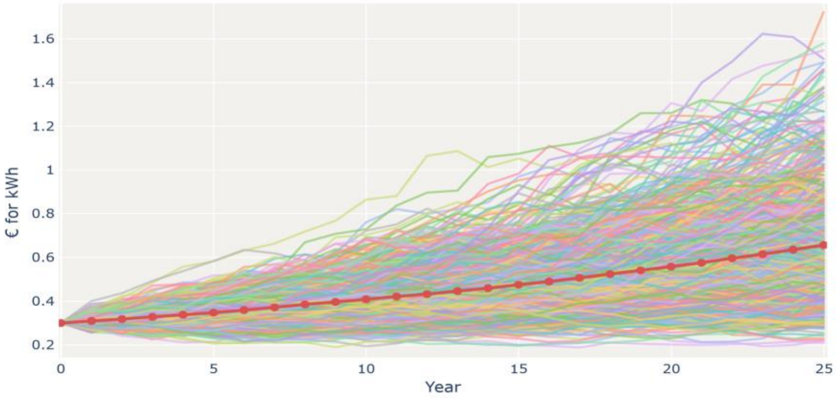
Electricity Tariff - Geometric Brownian Motion

$$dX_t = \mu X_t dt + \sigma X_t dB_t$$

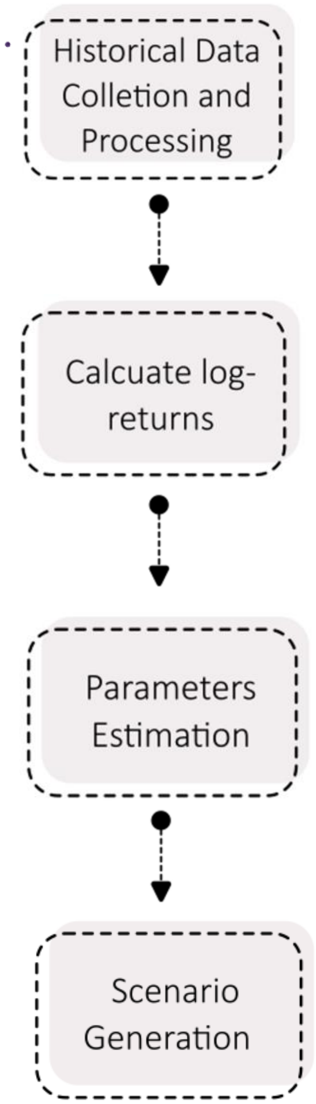
- Stochastic
- **Always positive**
- **Non-stationary**
- Continuous



Historical mean annual residential electricity prices (Author, 2024)



Generated Scenarios for training and evaluation (Author, 2024)



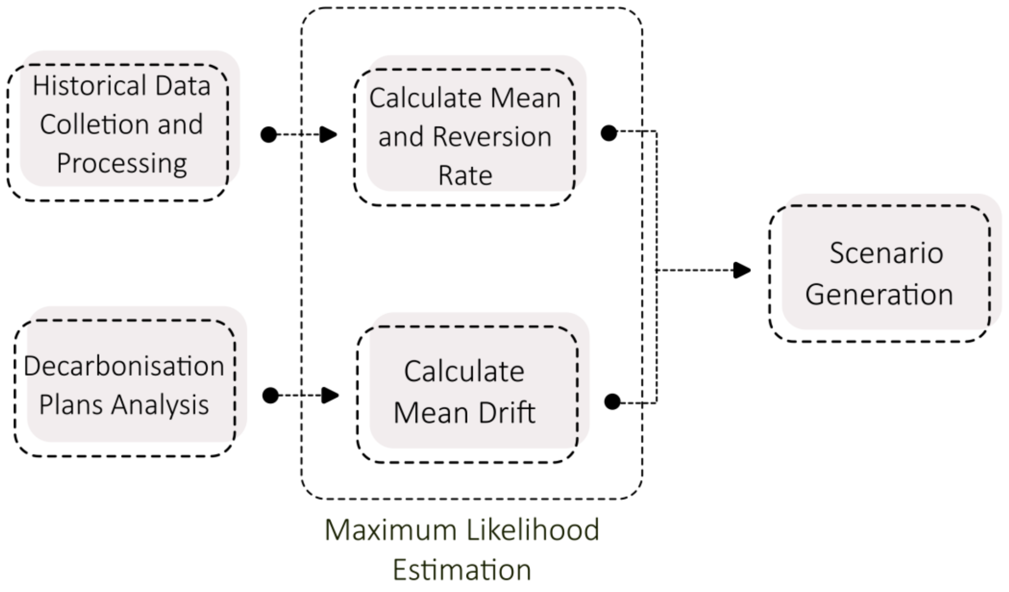
$$\mu = mean(logX_t) \times \frac{\sigma^2}{2} \qquad \sigma = \sqrt{var(logX_t)}$$

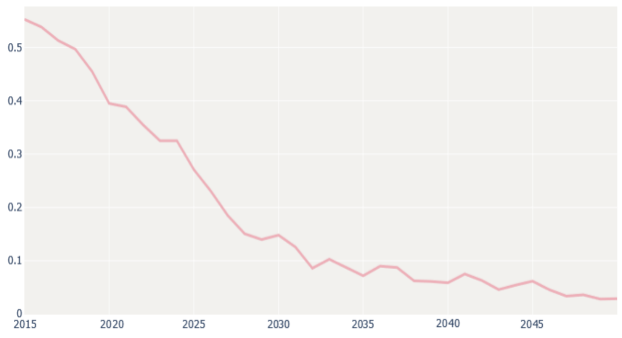
06 PV Optimisation

Grid Emissions Factor - Ornstein-Uhlenbeck Process

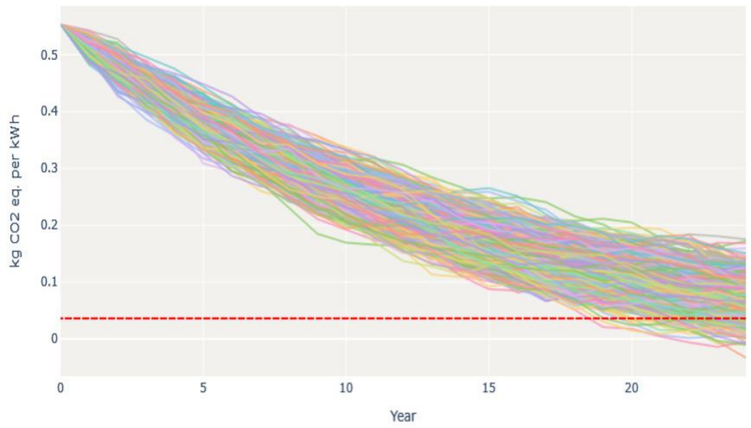
$$dX_t = \mu(\theta - X_t)dt + \sigma dW_t$$

- Stochastic
- **Mean Reversion**
- **Stationary**
- Continuous





Historical mean annual residential electricity prices (Author, 2024)



Generated Scenarios for training and evaluation (Author, 2024)

06 PV Optimisation

Crystalline Cell Efficiency Improvement - Gamma Process

- **Cumulative Process**
- **Positive Incremental Changes**
- Independent Increment
- Continuous

$$f(x;\ \alpha,\theta) = \frac{x^{\alpha(t-s)-1} e^{-\frac{x}{\theta}}}{\theta^{\alpha(t-s)}\Gamma(\alpha(t-s))}, \qquad x > 0$$

$$P_{PV,new}(t) = P_{PV,new}(t = 0) \times (Eff(t) + 1)$$

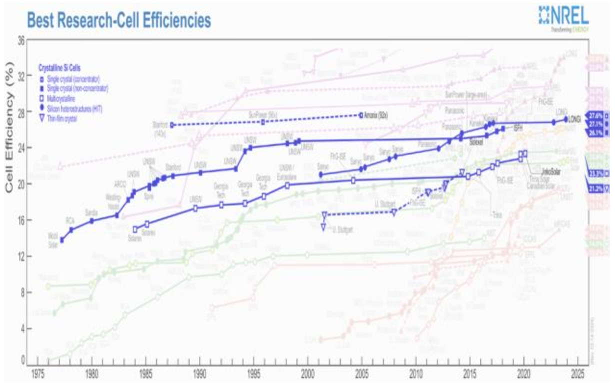
Historical Data Colletion and Processing

↓

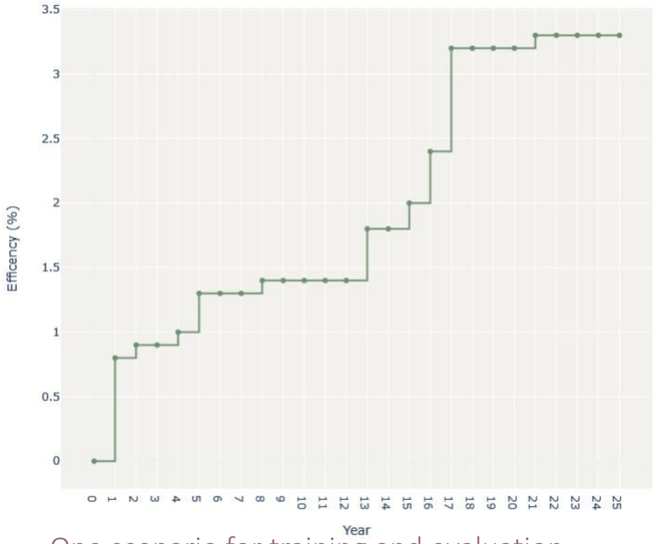
Parameters Estimation using Method of Moments

↓

Scenario Generation



Historical evolution of crystalline PV cell efficiency (Author, 2024)



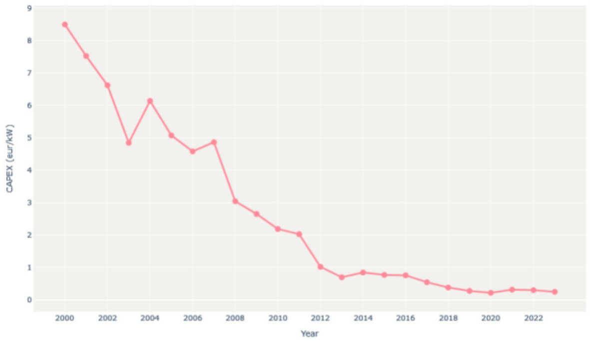
One scenario for training and evaluation (Author, 2024)

06 PV Optimisation

PV Module Price - Jump Diffusion Process (GBM with a Poisson process)

$$dX_t = \mu(t, X_t)\,dt + \sigma(t, X_t)\,dW_t + \sum_{j=1}^{N_t} Y_j\,dJ_t$$

- Stochastic
- Always positive
- Sudden Jumps
- Continuous



Historical CAPEX of PV modules €/kWp (Author, 2024)

Historical Data Collection and Processing

Parameters Estimation using MLE

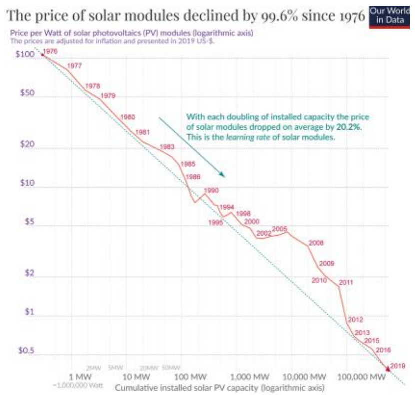
Scenario Generation

06 PV Optimisation

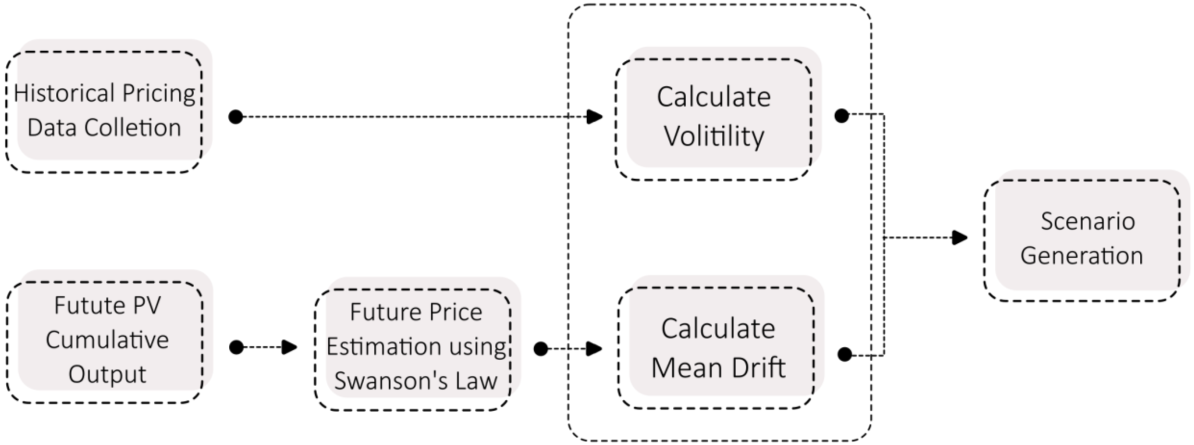
PV Module Price - GBM + Learning Rates

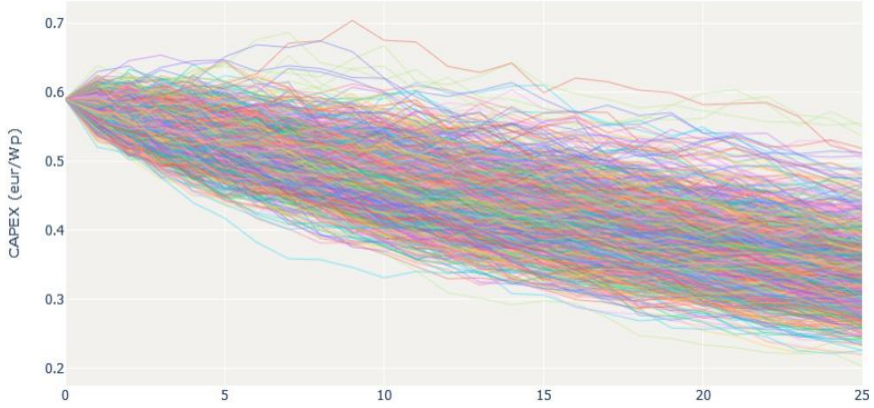
$$dX_t = \mu X_t dt + \sigma X_t dB_t \qquad C_Q = C_0 Q^{-\beta}$$

- Stochastic
- Always positive
- Continuous



(Roser, 2023)





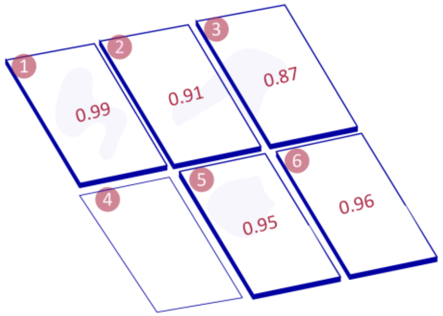
Generated Scenarios for training and evaluation (Author, 2024)

06 PV Optimisation

RL Environment – Observation Space

[Box/Multi-Continuous]

$$OBS(t) = [\eta_i(t), \eta_{i+1}(t), \ldots \eta_{i+n}(t), I(t), J(t), Eff(t),\ CAPEX_{PV}(t),$$
$$C(t-1), Pen(t), B(t), B(t-1), EG(t), id_i(t), id_{i+1}(t), \ldots id_{i+n}(t)]$$



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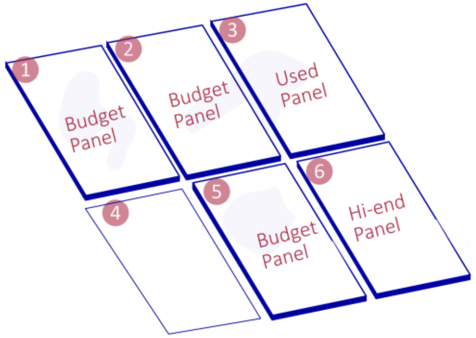


[0.99, 0.91, 0.87, 0, 0.95, 0.96]

System Performance

[PVCAPEX(t), FiT(t), Efficency(t), Grid CO2(t)]

External Conditions

[Expences(t-1), Interest(t), Budget(t-1), Budget(t)]

Internal Conditions

[0.6, 0.6 0.3, 0, 0.9, 0.9]

Panel Type ID's

06 PV Optimisation

Environment – Action Space

Simple Action

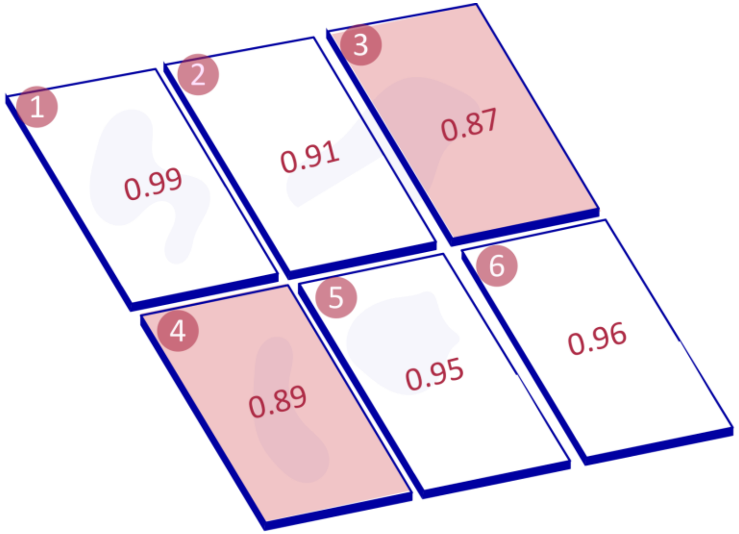
[Discrete / Multi-discrete)]

$$A = \{(x, y) \mid 0 \leq x \leq N \text{ and } 0 \leq y < M\}$$

Complex Action

[Multi-binary/ Multi-discrete]

$$A = \{ (x_i , x_{i+1} \dots x_n, y) \mid 0 \leq x_i \leq 1 \text{ and } 0 \leq y \leq M \}$$



$A_{simplified}$ = [2, 1]

A_{complex}= [0, 0, 1, 1, 0, 0, 1]

06 PV Optimisation

Environment – Reward

Financial Only

$$R_{FIN} = \sum_{t=1}^{25} BalanceFIN(t)$$

Mixed

$$R_{tot} = \sum_{t=1}^{25} Balance_{FIN}(t) \left[w + \sum_{t=1}^{25} Balance_{ENV}(t) \right]$$

System's Embodied Carbon

Grid Emission Factor

Module Cost

Installation Cost

Operational Costs

Balance of System Cost

Electricity Tariff

Resale Value

Budget

PV Yield

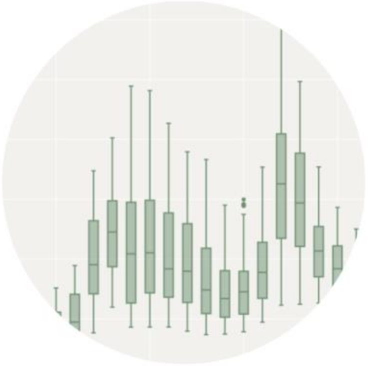
Self-Consumption and Export

Energy Export Consumption

Interest

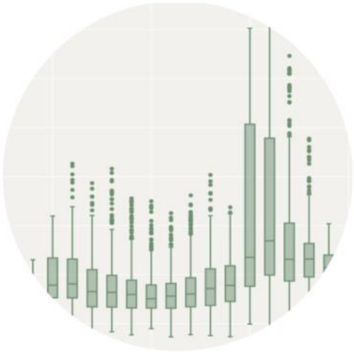
06 PV Optimisation

Analysed Scenarios – Houses



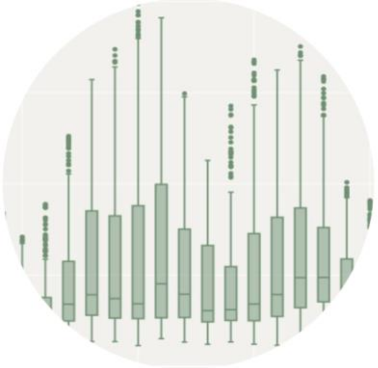
House 1

- Max no of modules: 12
- Annual Load: 3045 kWh
- Azimuth and Tilt: 180 and 40
- Single-Pitched



House 2

- Max no of modules: 24
- Annual Load: 3836 kWh
- Azimuth and Tilt: 180 and 30
- Single-Pitched



House 3

- Max no of modules: 32
- Annual Load: 4678 kWh
- Azimuth and Tilt: 90/270 and 30
- Double-Pitched

06 PV Optimisation

Analysed Scenarios – Modules

Second-Hand Module
Polycristaline
- Carbon Footprint: None
- Efficiency: 16.2%
- CAPEX(t=1): 0,36 €/Wp
- Mean Degradation: 1.16%

Budget Panel
Monocristaline, PERC
- Carbon Footprint:
- Efficiency: 21.3%
- CAPEX (t=1): 0,69 €/Wp
- Mean Degradation: 0.82%

High-End Panel
Monocristaline, N-type, IBC
- Carbon Footprint:
- Efficency: 23.3%
- CAPEX(t=1): 1,583 €/Wp
- Mean Degradation: 0.67%

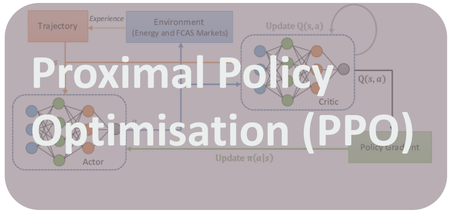
Select Panel

Low
- Min at t=1: 0 €
- Min at t=1: 750 €

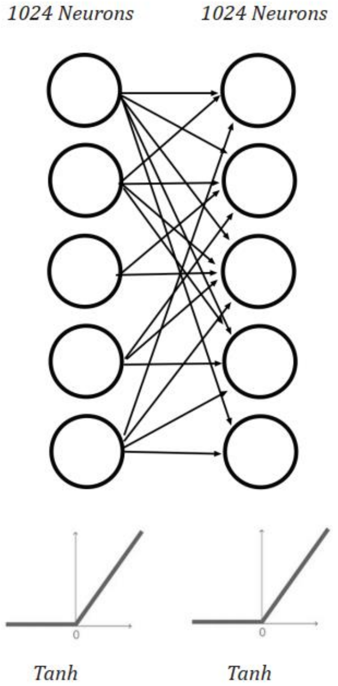
High
- Min at t=1: 750 €
- Min at t=1: 2000 €

06 PV Optimisation

Hyperparameters Tuning



No of Neurons	1024
No of Layers	2
Activation Function	Tanh
Learning Rate	Linear decay from 0.0003 to 0.00001
No of Steps	2048
Gamma	0.99
Lambda	0.93
Batch Size	1024
Clip Ratio	0.17
Entropy coefficient	0.0
No of Epochs	24



OPTUNA

Algorythm Selection → Environment Vectorisation for multiprocess → Automatic tuning → Manual Tuning

06 PV Optimisation
Evaluation

40x

Trained Model

VS

Base Policy

Common Practice

$if\ \eta_i < 0.85 \quad install\ panel\ i$

Training : Evaluation

7 : 3

Evaluation Metrics

Net Present Value

$$NPV = \sum_{t=0}^{T} \frac{Balance_{NPV}(t)}{(1+\vartheta)^t}$$

Net Carbon Savings

$$NCS = \sum_{t=1}^{T} Balance_{ENV}(t)$$

06 PV Optimisation

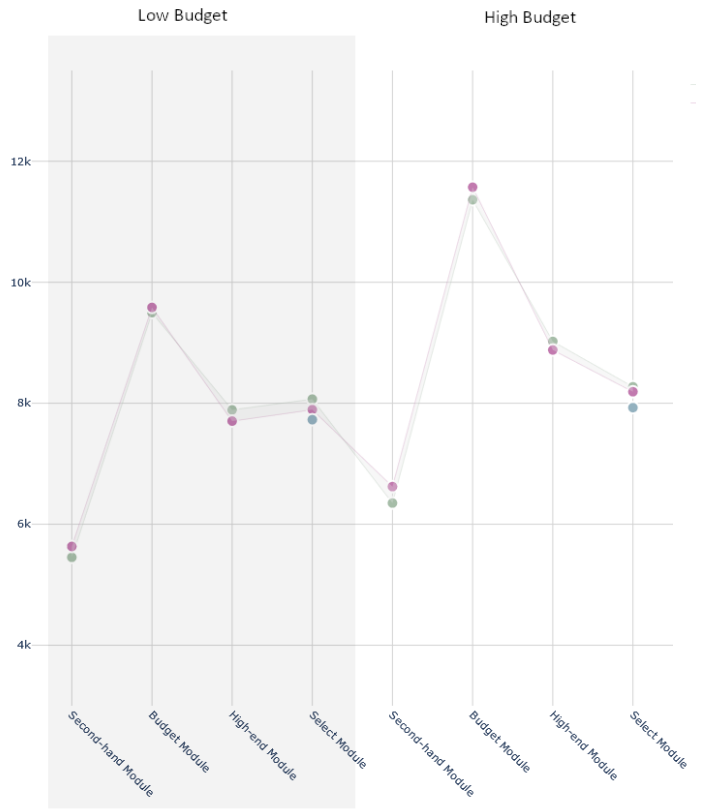
Results – Key Figures (financial reward only)

	Mean NPV	Mean PV production	Average Efficiency During Module's	Mean Interest
Simple Action Space Vs Base Policy	+6.4%	-4%	-6 p.p.	-9%
Complex Action Space Vs Base Policy	-18%	-17%	-8 p.p.	+14%

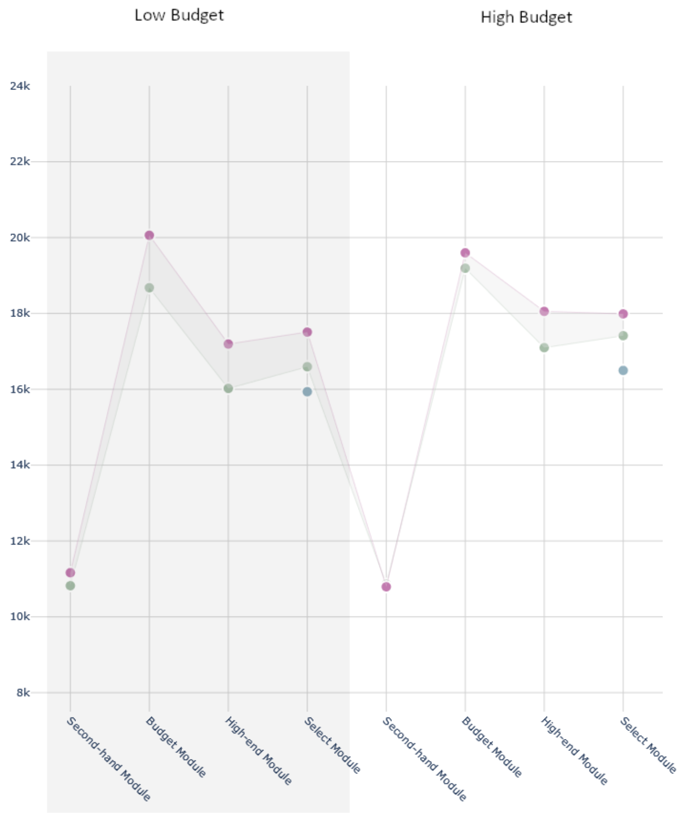
06 PV Optimisation

Results – Overview NPVs

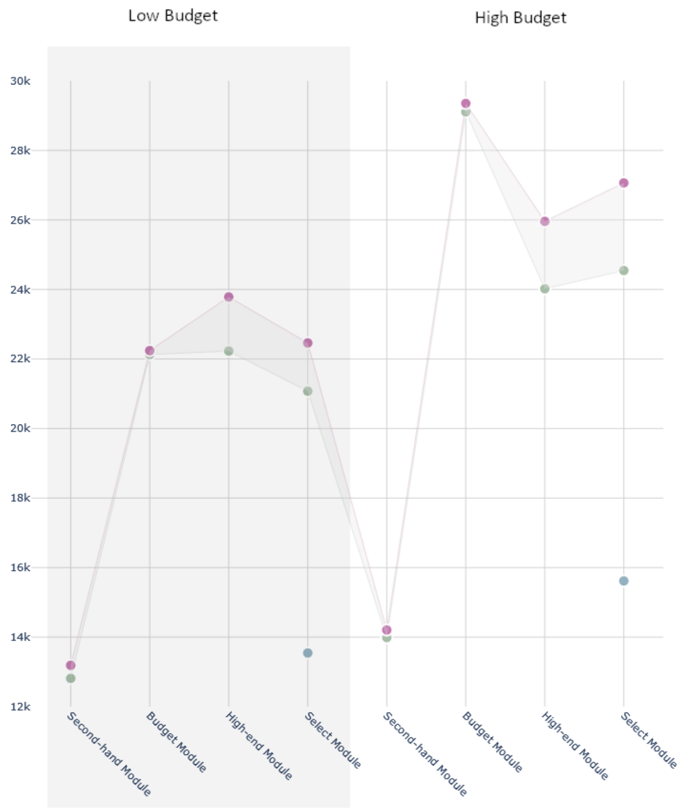
Base Policy
Simple Action
Complex Action



House 1 – 12 modules



House 2 – 24 modules



House 3 – 32 modules

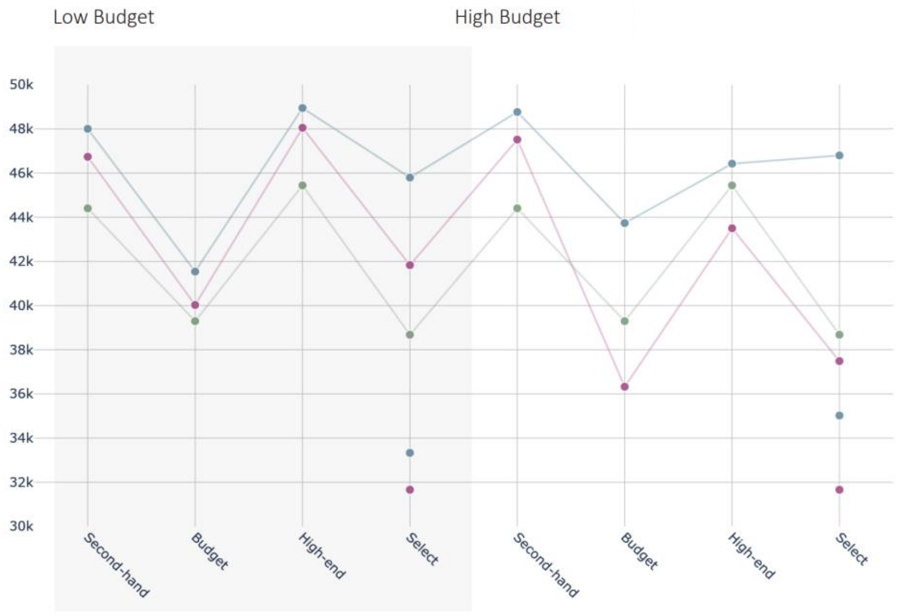
06 PV Optimisation

Results – House 3 Comparison

Mean	Financial Reward Only	Mixed Reward (Financial + Environmental)
NPV	+7.4%	-1.3%
NCS	+0.9%	+9.8%

Vs Base Policy (Simple Action Only)

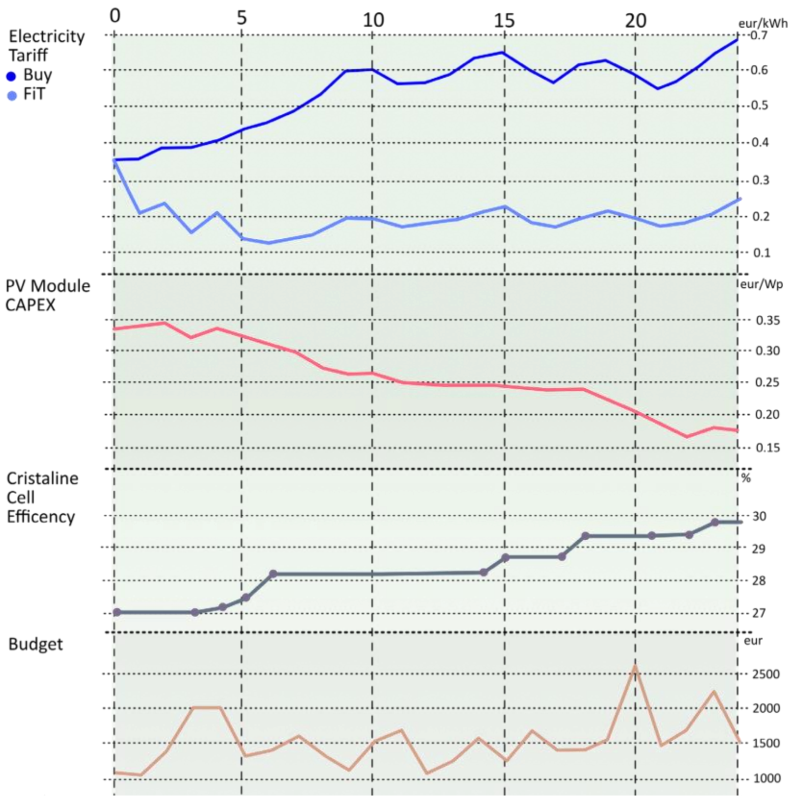
Plot of NPVs for each analysed scenario for House 3

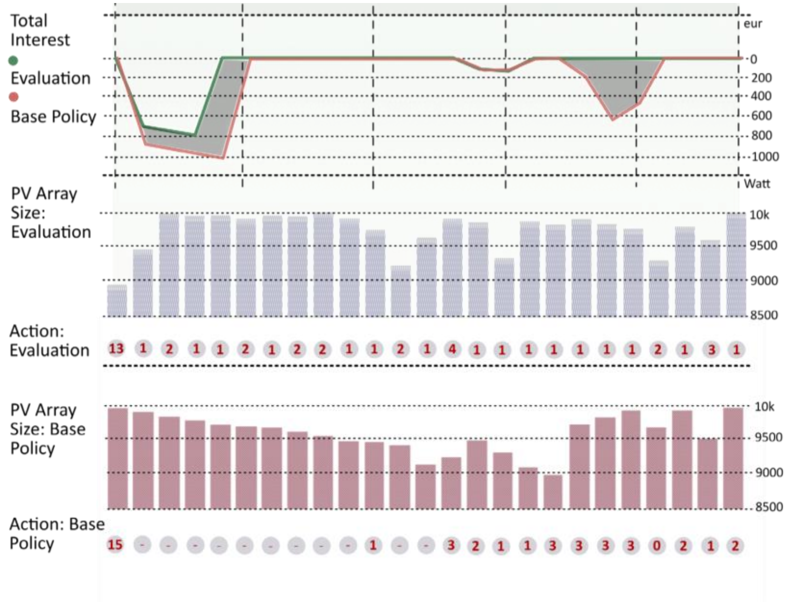


Plot of NCSs for each analysed scenario for House 3

06 PV Optimisation

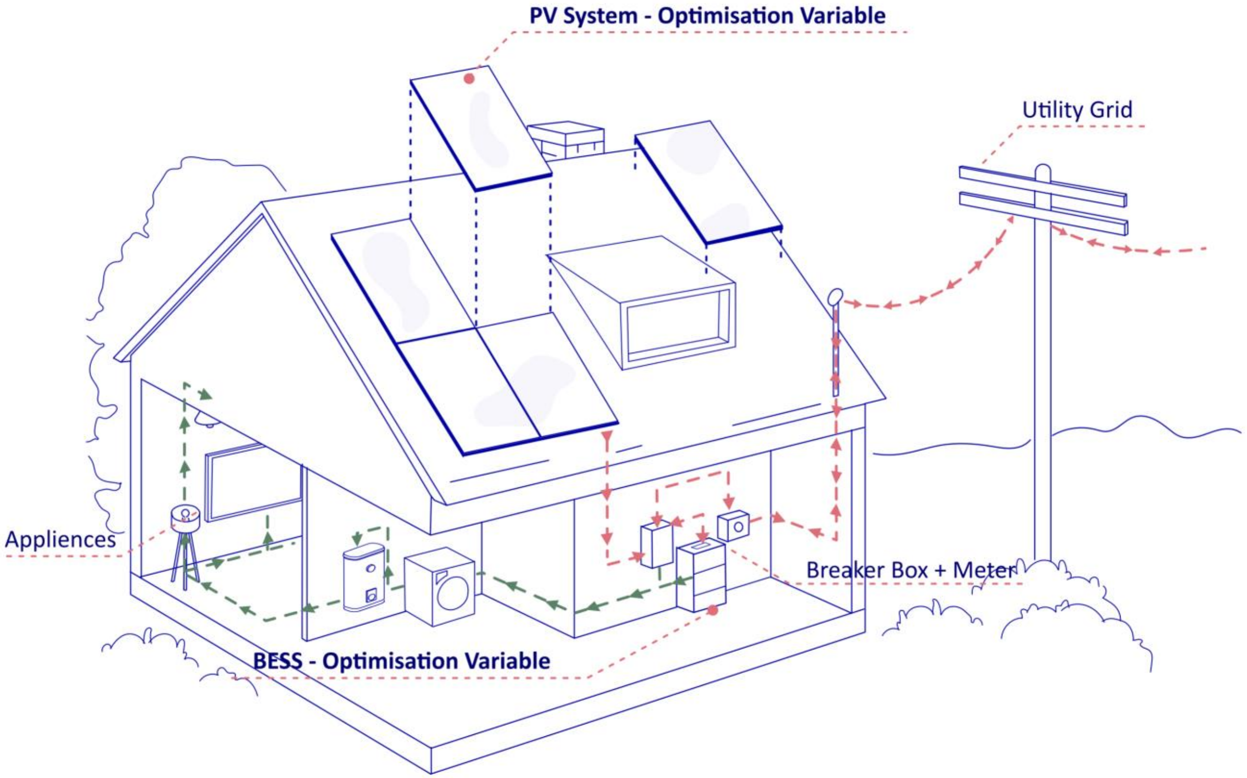
Results – Selected Episode



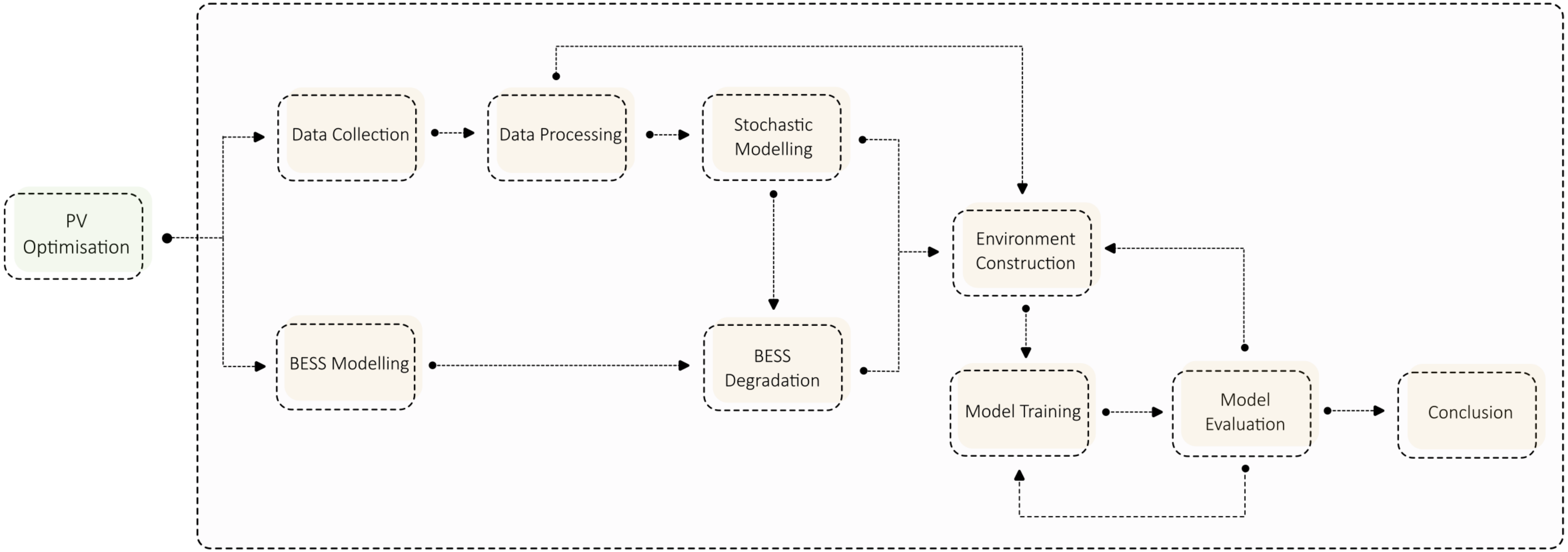


-	Achieved NPV
Model Evaluation	22 486
Base Policy	20 364

07
PV+ BESS Optimisation

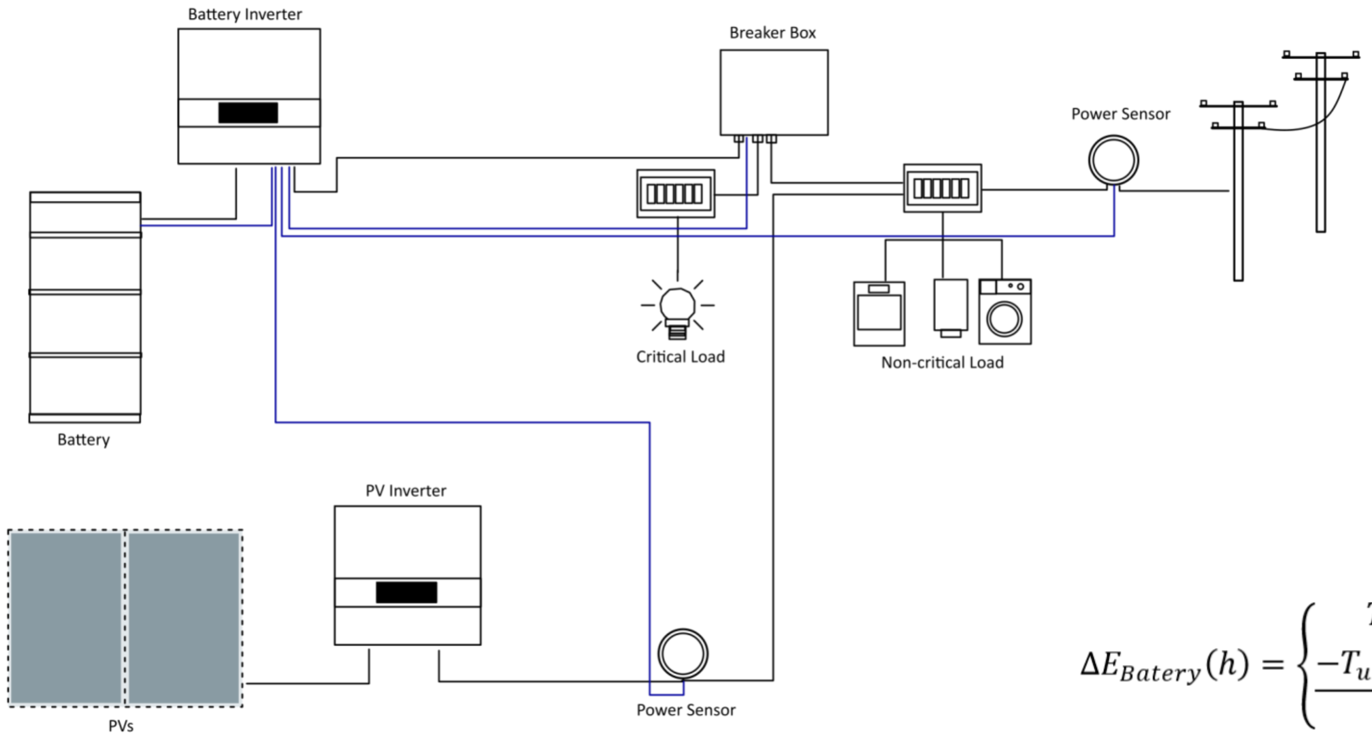


07 PV + BESS Optimisation



07 PV + BESS Optimisation

System Modelling



System under consideration (Author, 2024)

$$\Delta E_{Batery}(h) = \begin{cases} T_u Q_{charge}(h)\eta_c & \text{if charging} \\ \dfrac{-T_u Q_{discharge}(h)}{\eta_d} & \text{if discharging} \end{cases}$$

$$E_{Batery}(h+1) = E_{Batery}(h)(1-\eta_{p,leak}) + \frac{\Delta E_{Batery}(h)}{\eta_{inv,B}} - T_u \times \eta_{c,leak}$$

07 PV + BESS Optimisation

Battery Operation - How to schedule battery’s charge and discharge?

Fluctuating PV Production and Consumption

Varying Electricity Tariff

- **Peak Shaving**

  Reducing the consumption of electricity from the grid during peak demand and high rates

- **Load Shifting**

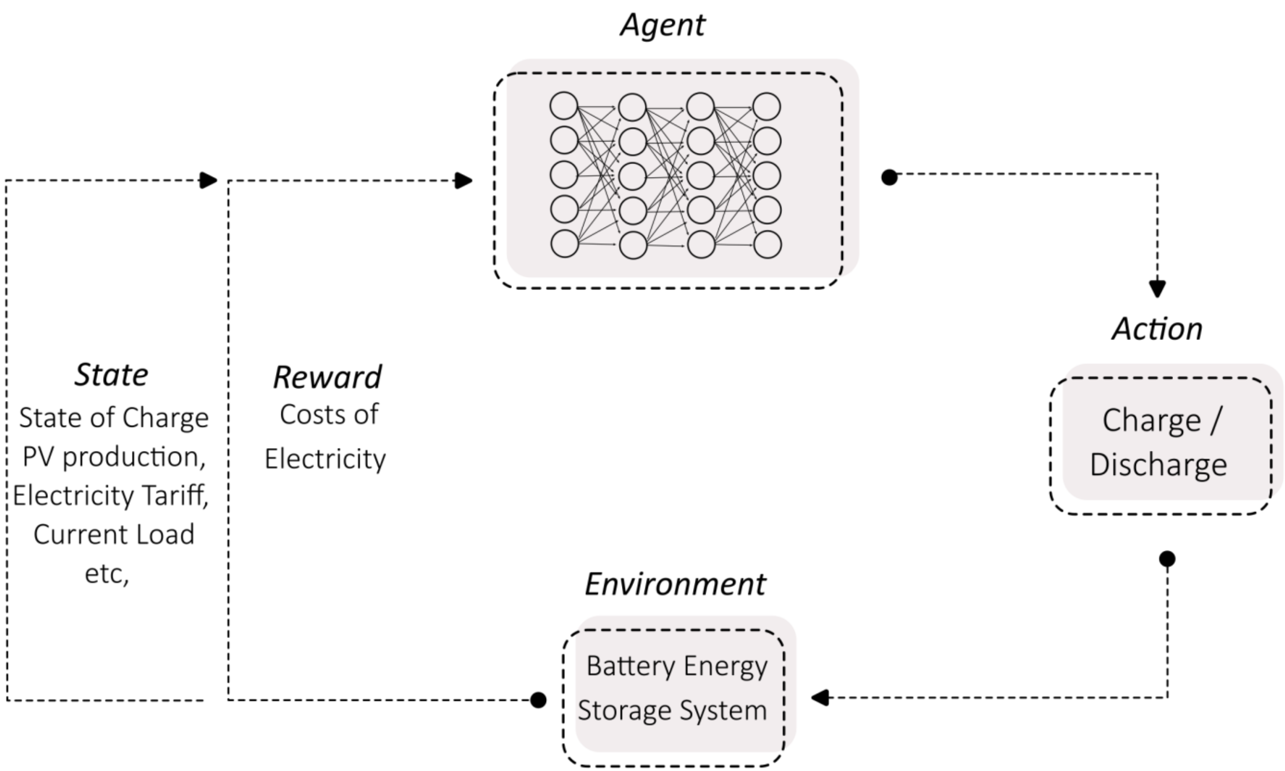
  Charging the battery when demand and electricity rates are low

- Battery Health Management

- Linear Programming
- Nonlinear programming
- Dynamic Programming
- Rule-Based Control

07 PV + BESS Optimisation

Battery Operation - RL



- Develop the optimal schedule for battery's charge and discharge
- Generalise Over Different Battery sizes, Load Consumptions and PV array sizes

07 PV + BESS Optimisation

Battery Operation – RL Environment

Observation (State) Space
[Box/Multi-Continuous)]

$$OBS(h) = [SOC(h),\ SOC(h-1),\ N(h),\ N(h+1),\ N(h+2),\ I(h),\ J(h),\ Hour,\ Week,\ B_{cap},\ P_{max}]$$

$$N(h) = P_{PV,total} - P_{load}$$

Episode Time Horizon
168 hourly timesteps

Reward

$$R = [-I(h) \times E_{sup}(h) + J(h) \times E_{exp}(h)]$$

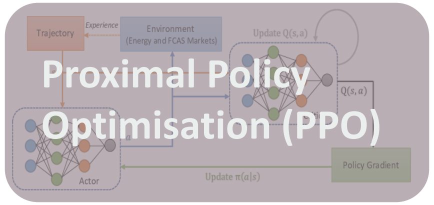
Action Space
[Continuous]

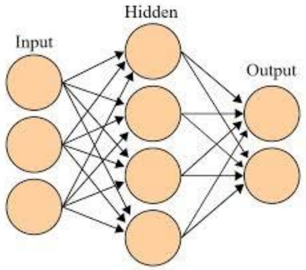
$$A = [Q_{discharge,max} \quad Q_{charge,max}]$$

Gymnasium

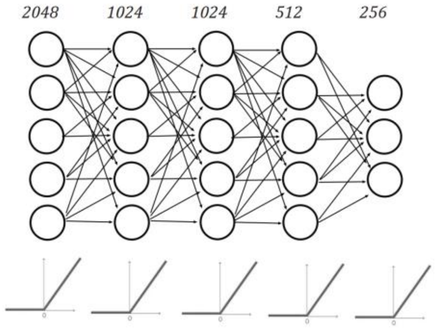
07 PV + BESS Optimisation

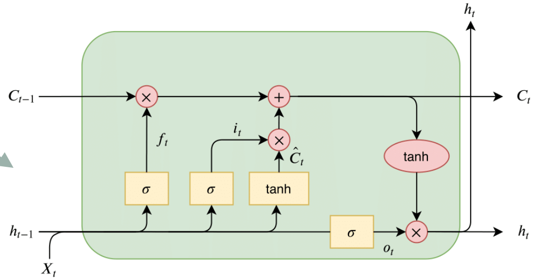
Battery Operation – RL Models





Dense NN





LSTM

Network Selection → Automatic Tuning → Manual Tuning

OPTUNA

RLlib

07 PV + BESS Optimisation

Battery Operation – RL Evaluation

Trained Model
House 1

VS

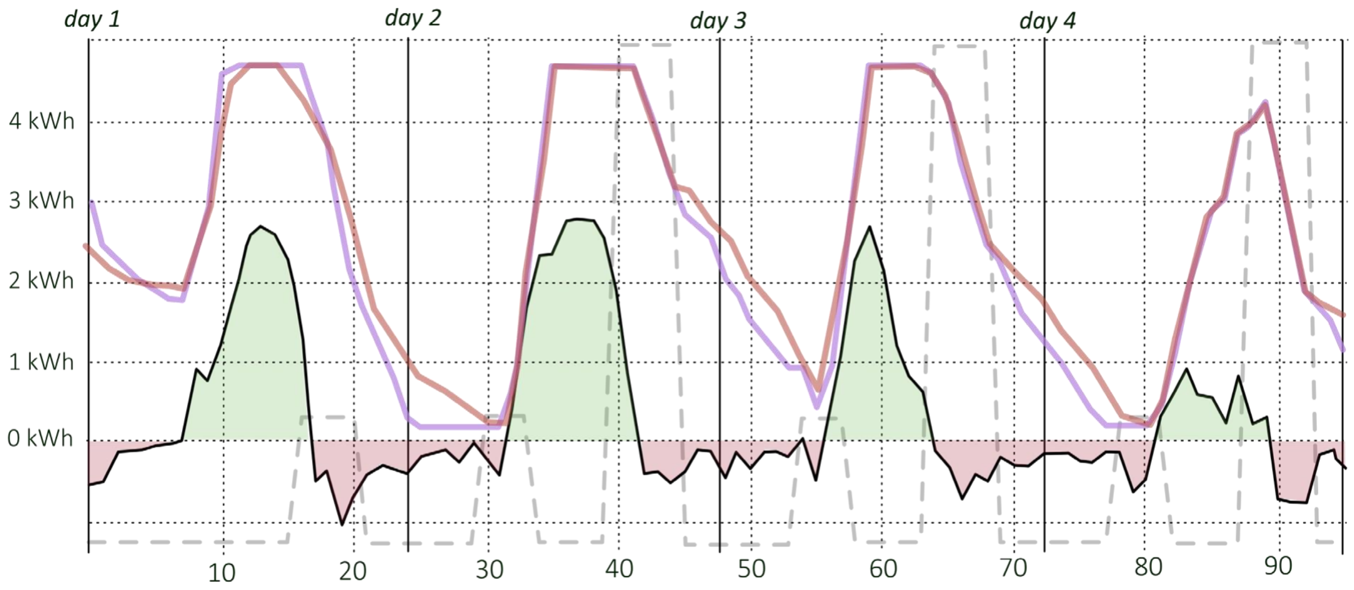
Rule-Based Control

$$if\ N(h) < 0 \quad discharge$$
$$if\ N(h) > 0 \quad charge$$

07 PV + BESS Optimisation

Battery Operation – RL Results

No Battery	Rule-based	RL Model
-949.7 EUR	-121.4 EUR	-108.9 *EUR*

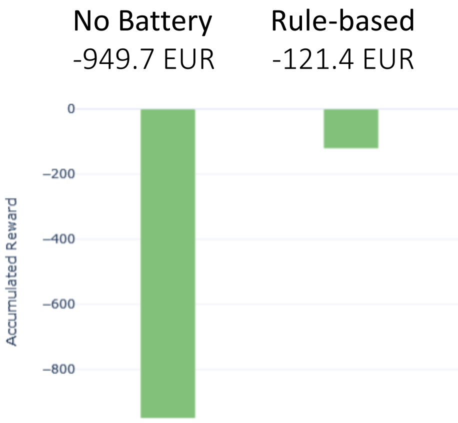


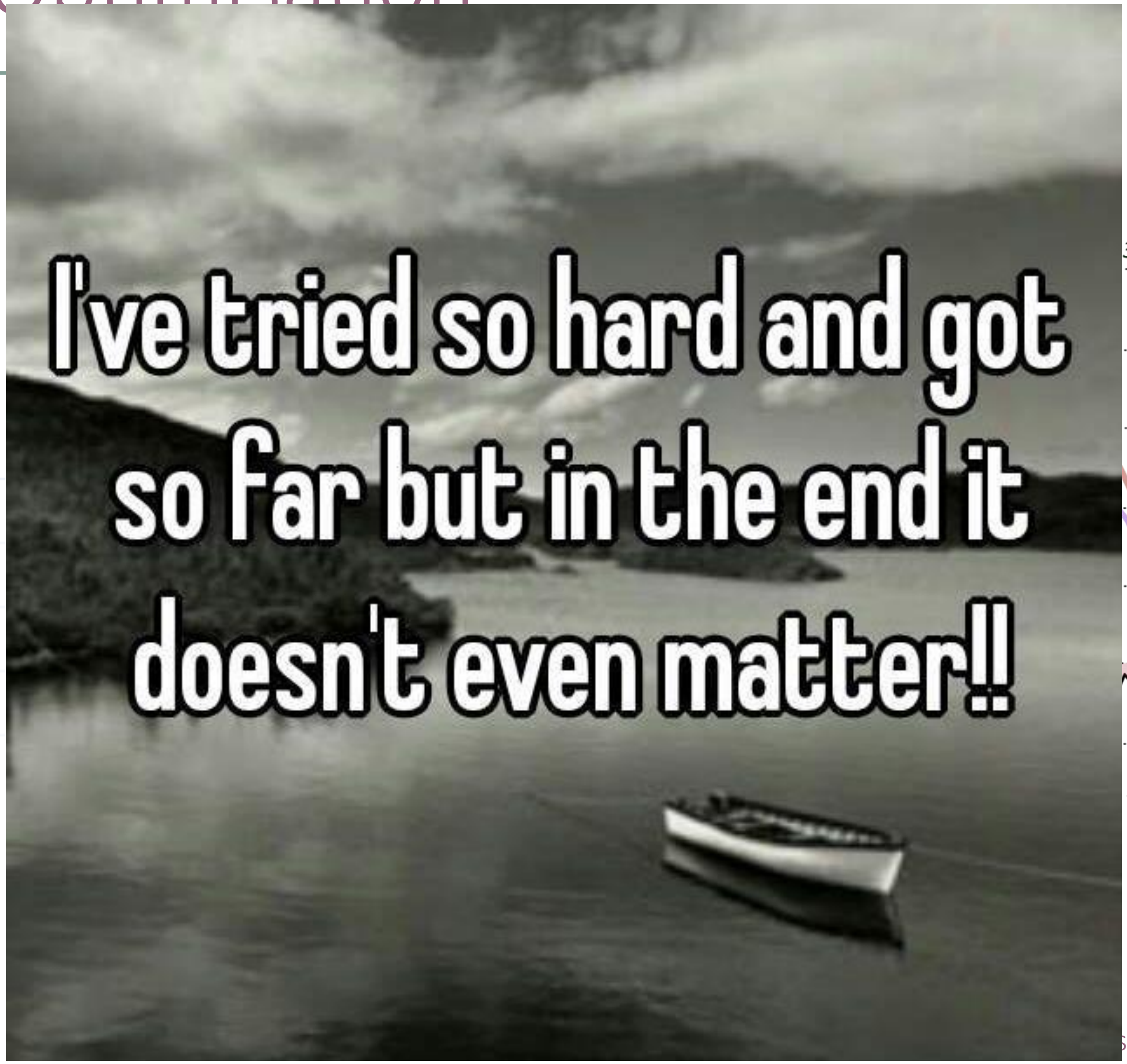
SoC of the Battery plotted for a Week

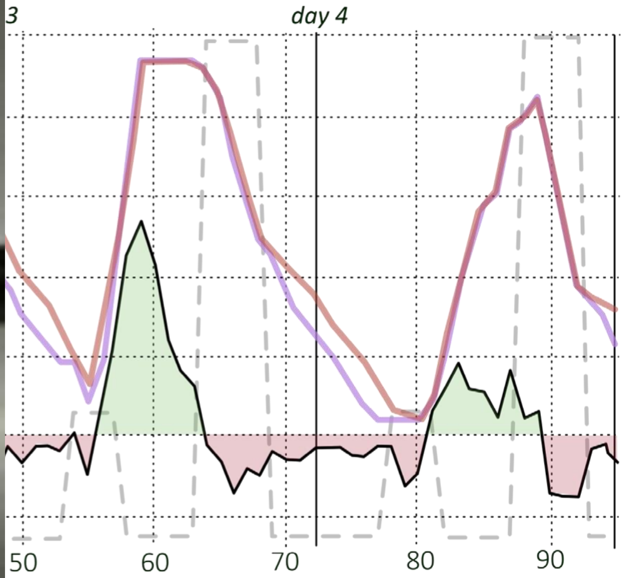
red line - RL operated BESS,
purple - rule-based operation,
dashed line - electricity tariff rates,
red and green fields - electricity shortage or surplus from PV and building load

07 PV + BESS Optimisation

Battery Operation –







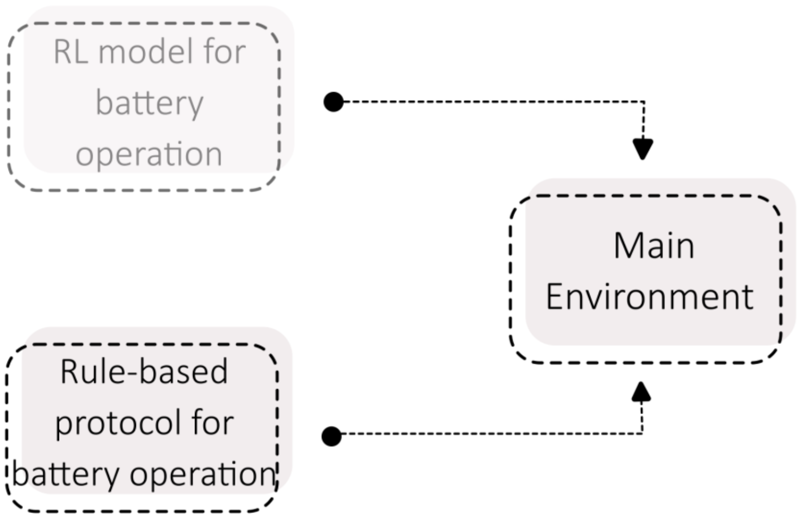
from PV and building load

07 PV + BESS Optimisation

Battery Operation – RL Reality Check

Training Time (house 1 – main model)

- No BESS environment - t
- Rule Based BESS operation – **t x 6**
- RL based BESS operation – **t x 25**

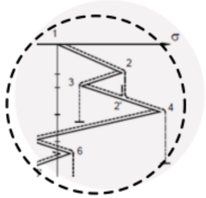


07 PV + BESS Optimisation

Battery Degradation – Non-linear Gamma Process

$$f_{a,b}(x) = \frac{1}{\Gamma(a\varphi(t))} b^{a\varphi(t)} x^{a\varphi(t)-1} e^{-bx}$$

$$SoH = \frac{B_{cap,act} - B_{cap,EOL}}{B_{cap,nom} - B_{cap,EOL}} \times 100\%$$



Rainflow Cycles Couting

Literature Review

Educated Guess

Dataset Selection and Processing

Parameter Estimation

Scenario Generation

Annual Degradation Determination

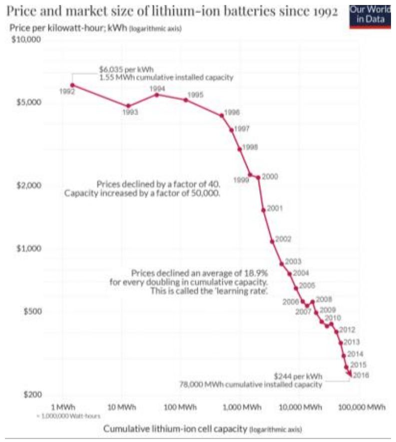
A plot of 100 NHGP for the battery degradation paths (Author, 2024)

07 PV + BESS Optimisation

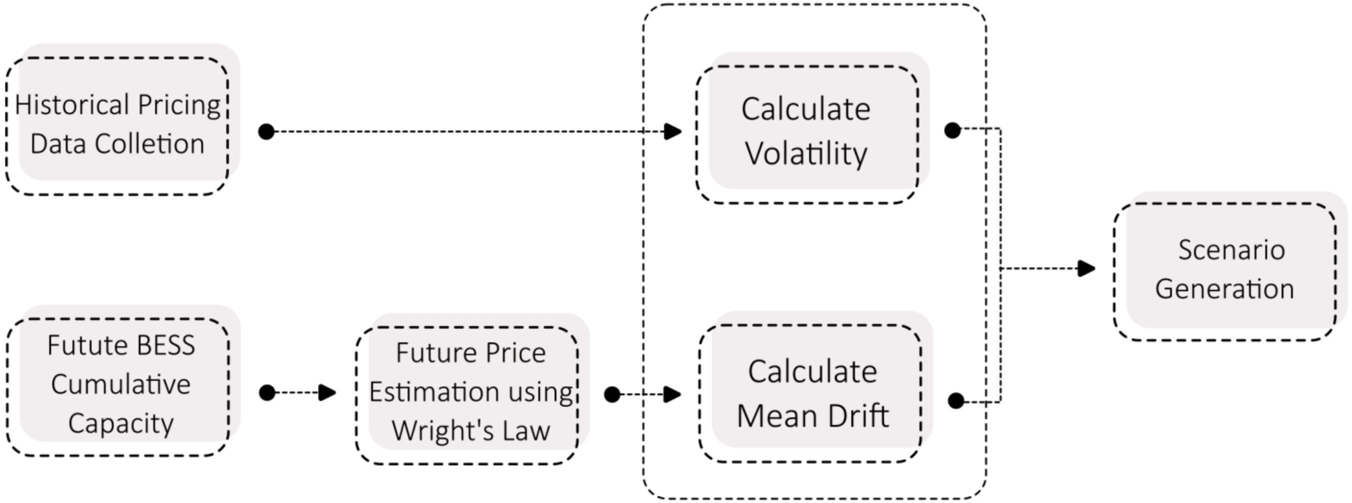
Battery Price - GBM + Learning Rates

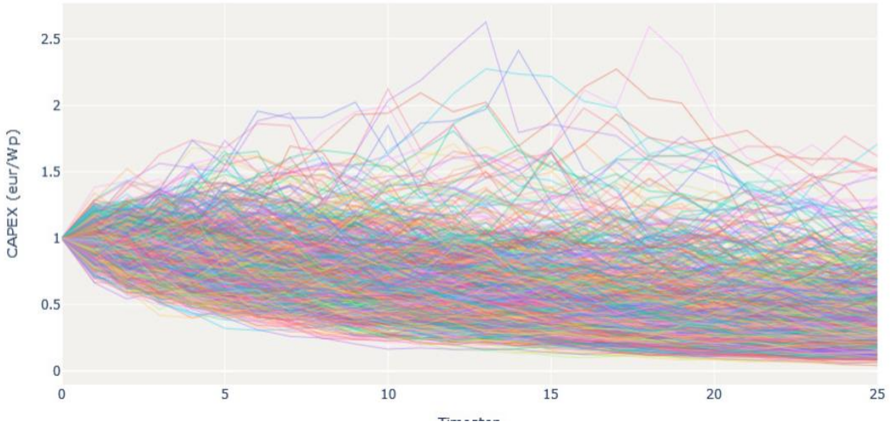
$$dX_t = \mu X_t dt + \sigma X_t dB_t$$

- Stochastic
- Always positive
- Continuous



(Ritchie, 2023)





07 PV + BESS Optimisation

Environment

Observation (State) Space
[Box/Multi-Continuous)]

$$OBS(t) = [\eta_i(t), \eta_{i+1}(t), \dots \eta_{i+n}(t), I(t), J(t), Eff(t),\ CAPEX_{PV}(t),$$
$$C(t-1), Pen(t), B(t), B(t-1), EG(t), id_i(t), id_{i+1}(t), \dots id_{i+n}(t),$$
$$B_{cap}(t) \times SoH(t), CAPEX_{BAT}(t)]$$

State of Health of Each Battery Module

Battery Price

Action Space
Simple Action
[Multi-discrete]

$$A = \{(x, y, z) \mid 0 \le \mathrm{x} \le \mathrm{N} \text{ and } 0 \le \mathrm{y} \le \mathrm{M} \text{ and } 0 \le \mathrm{z} \le \mathrm{L}\}$$

Complex Action
[Multi-discrete]

$$A = \{(x_i, x_{i+1} \dots x_n, y, z) \mid 0 \le \mathrm{x}_i \le 1 \text{ and } 0 \le \mathrm{y} \le \mathrm{M} \text{ and } 0 \le \mathrm{z} \le \mathrm{L}\}$$

07 PV + BESS Optimisation

Evaluation

30x

Trained Model

VS

Base Policy

Common Practice

$$if\ \eta_i < 0.8 \qquad install\ panel\ i$$

$$if\ B_{cap,j} = 0 \qquad install\ battery\ module\ j$$

Reward

$$R_{FIN} = \sum_{t=1}^{25} BalanceFIN(t)$$

Training : Evaluation

7 : 3

Evaluation Metrics

Net Present Value

$$NPV = \sum_{t=0}^{T} \frac{Balance_{NPV}(t)}{(1+\vartheta)^t}$$

07 PV + BESS Optimisation

Results – Key Figures

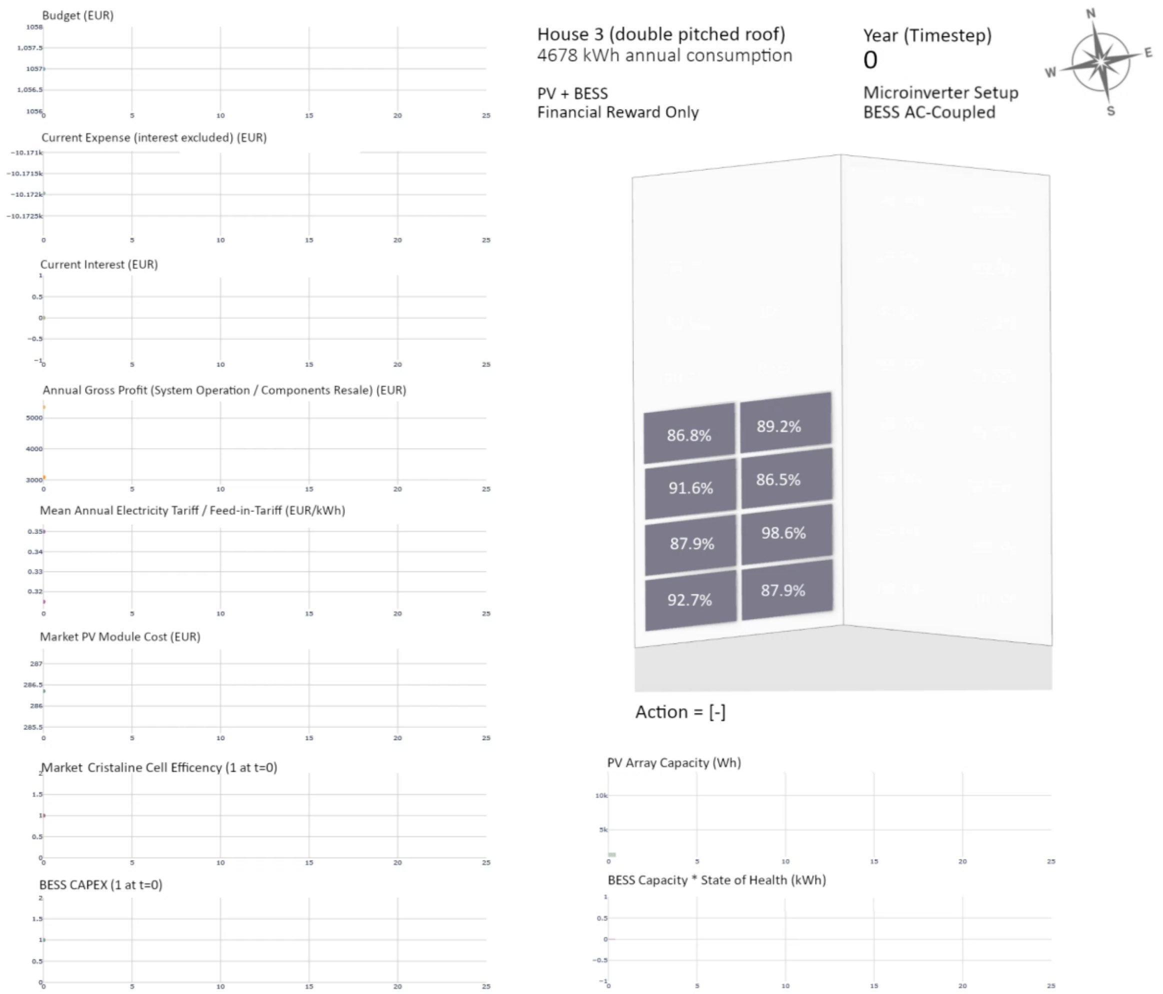
	Mean NPV	Mean PV production	Mean Self-consumption	Mean Interest
Simple Action Space Vs Base Policy	+16%	-4%	-12%	-31%
Complex Action Space Vs Base Policy	-12%	-17%	-22%	-1%

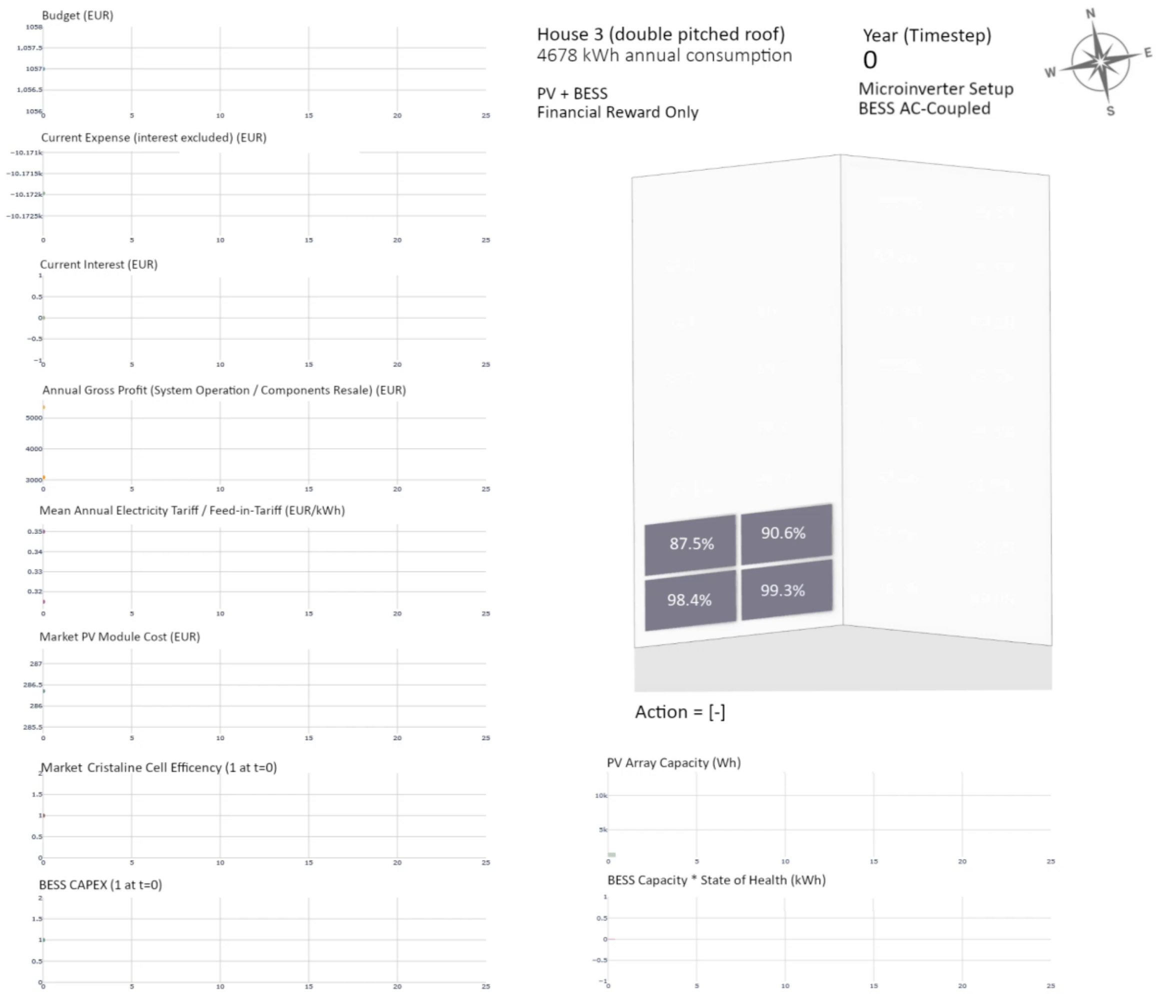
07 PV + BESS Optimisation

Results – NPVs Overview

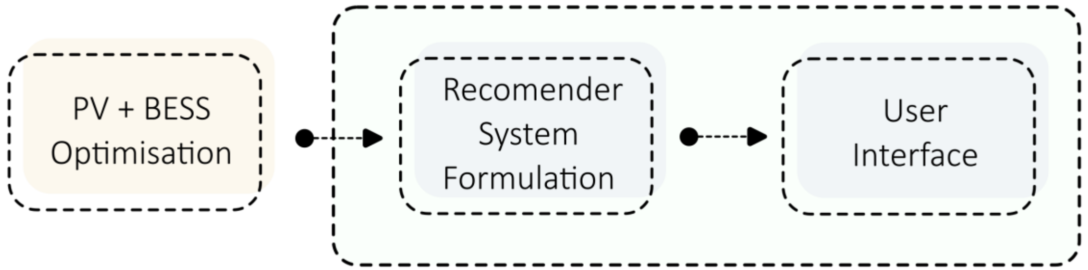
07 PV + BESS Optimisation

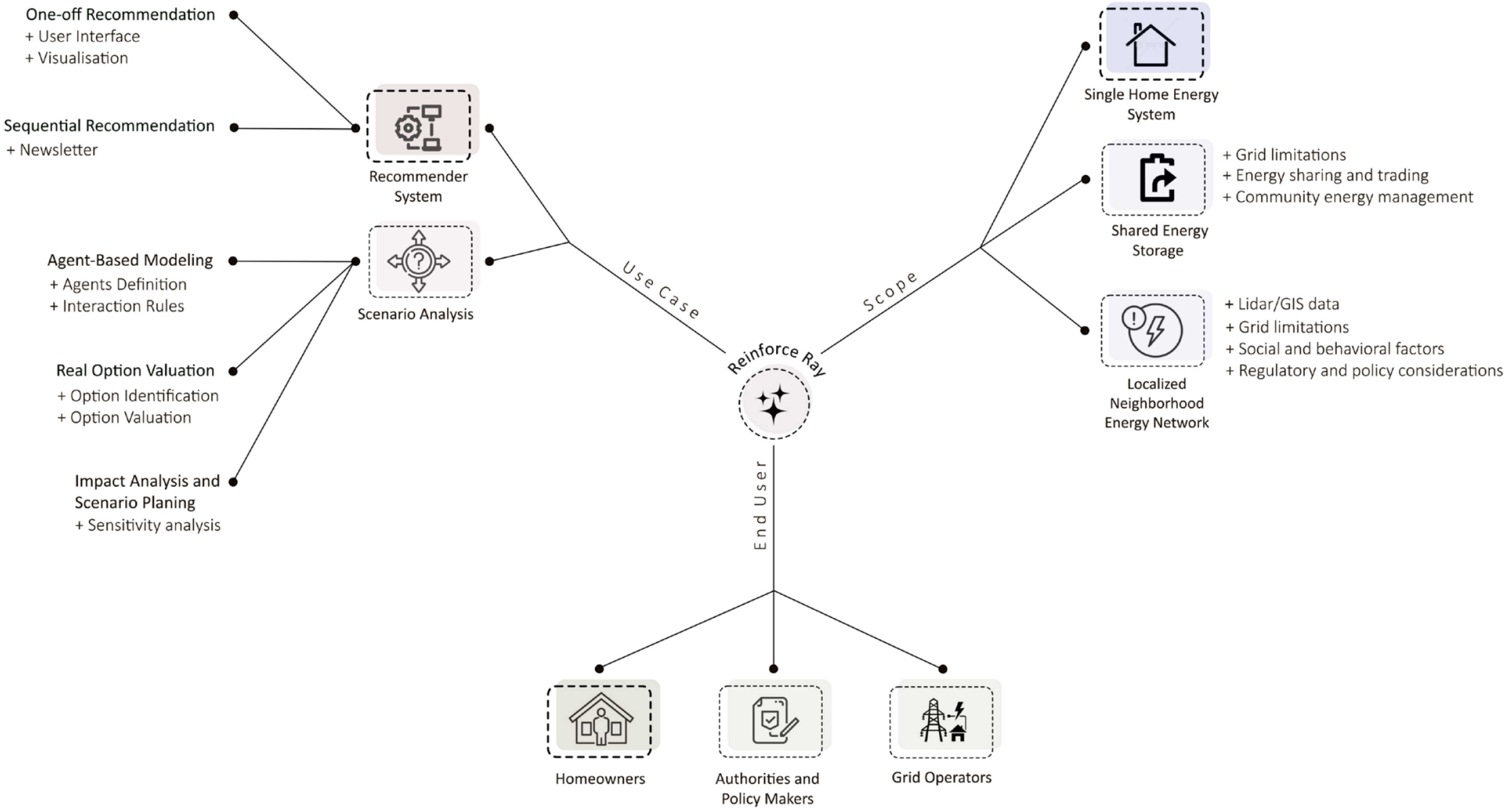
Results – Selected Episode





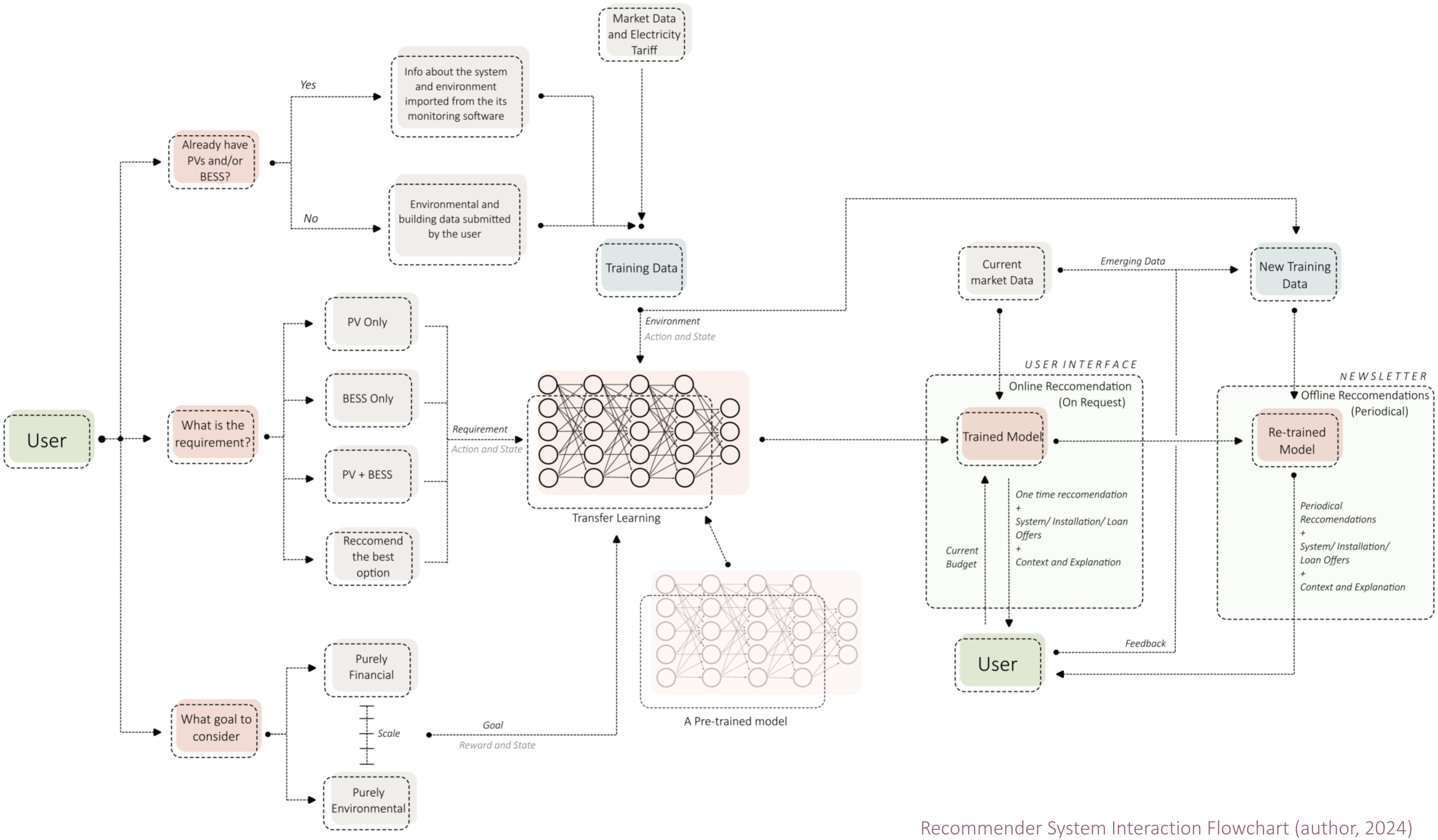
08 Deployment




One-off Recommendation
+ User Interface
+ Visualisation
Sequential Recommendation
+ Newsletter
Recommender System
Agent-Based Modeling
+ Agents Definition
+ Interaction Rules
Scenario Analysis
Real Option Valuation
+ Option Identification
+ Option Valuation
Impact Analysis and Scenario Planing
+ Sensitivity analysis
Use Case
Reinforce Ray
Scope
Single Home Energy System
Shared Energy Storage
+ Grid limitations
+ Energy sharing and trading
+ Community energy management
Localized Neighborhood Energy Network
+ Lidar/GIS data
+ Grid limitations
+ Social and behavioral factors
+ Regulatory and policy considerations
End User
Homeowners
Authorities and Policy Makers
Grid Operators

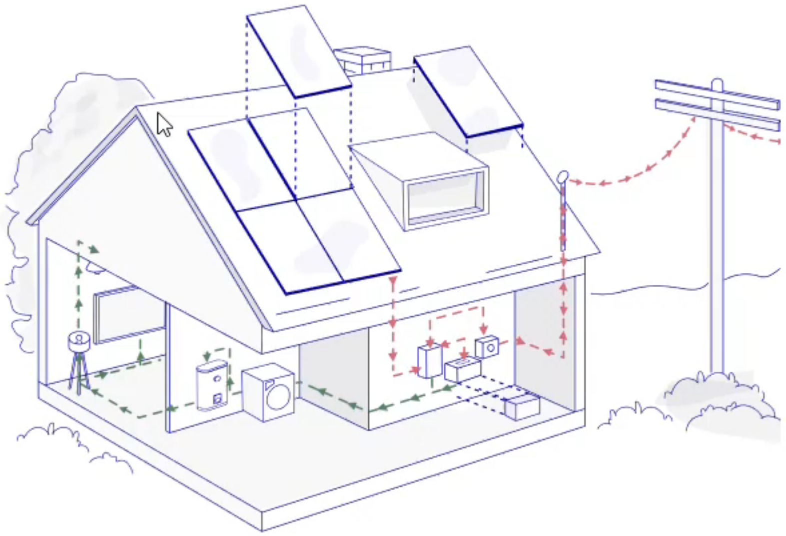
08 Deployment

Recommender System



Recommender System Interaction Flowchart (author, 2024) reinforce ray About Find Installers Contact Get Started

Reinforce Ray is a recommender system, utilising the power of **AI** to supply you with optimal guidance for upgrading your **home renewable energy setup**.



Reinforce Ray is suitable for:

- PV or Battery only and PV+Battery setups
- Single house and neighborhood energy systems
- Existing systems' upgrade and completely new setups

Every recommendation stems from analyzing millions of scenarios based on relevant conditions and variables.

Define your needs and scope – we'll assist you in making an informed decision and planning for the future. Our system will help you determine the optimal size and type of energy storage and PV system.

A bespoke AI model is trained to your specifications, taking into account:

- Your budget options
- Installation and components costs.
- Consumer electricity market conditions
- Latest advancements in technology.

08 Deployment

User Interface

10 Conclusion

Overall, it can be concluded that reinforcement learning is a viable framework for the planning and design of residential grid-connected PV and BES systems. The deployment of this workflow into practice can have several benefits for stakeholders and decision-makers.

- **Make better decisions that both save money and reduce carbon emissions**
- **More Informed Decision-Making**
- **Strategic flexibility allowing to modify or defer plans in response to the arrival of new information**
- **Support multi-stage investment with expansion or contraction options**
- **Risk Mitigation - Asses the value of different strategies under uncertainty**

11 Further Research

Benchmark Against Other Computational Approaches

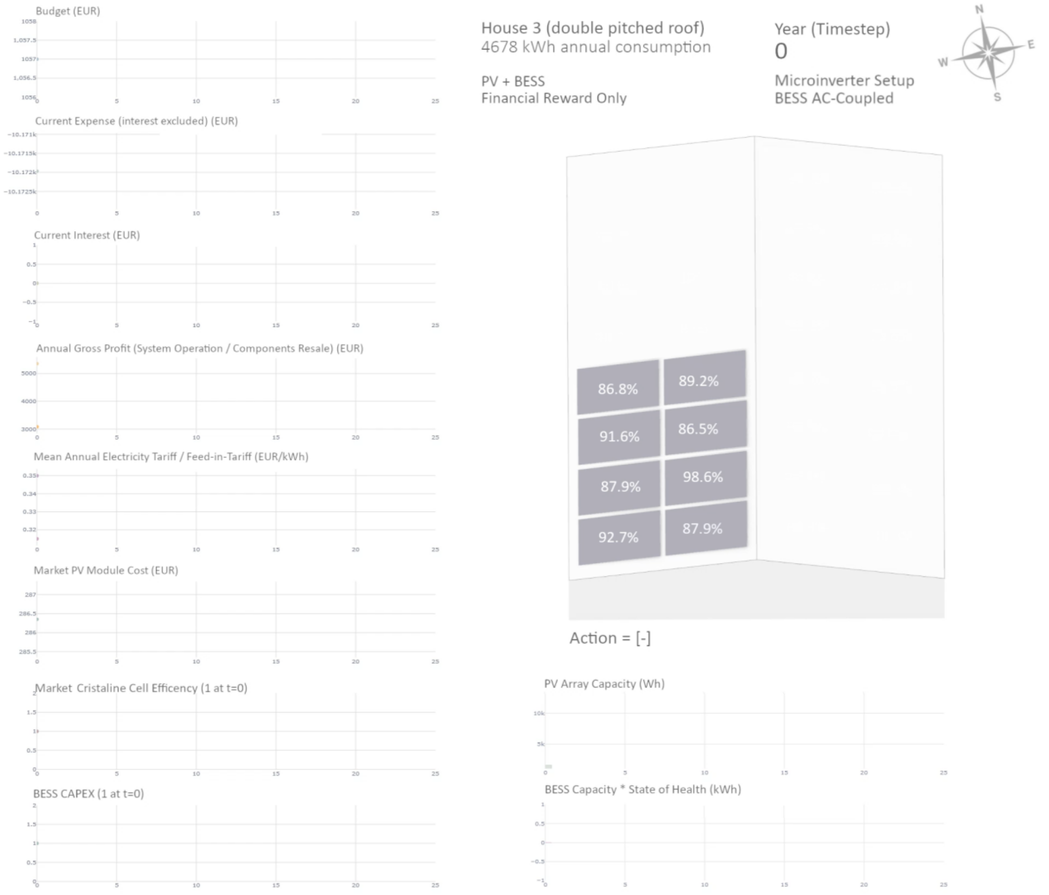
Reevaluate Probabilities

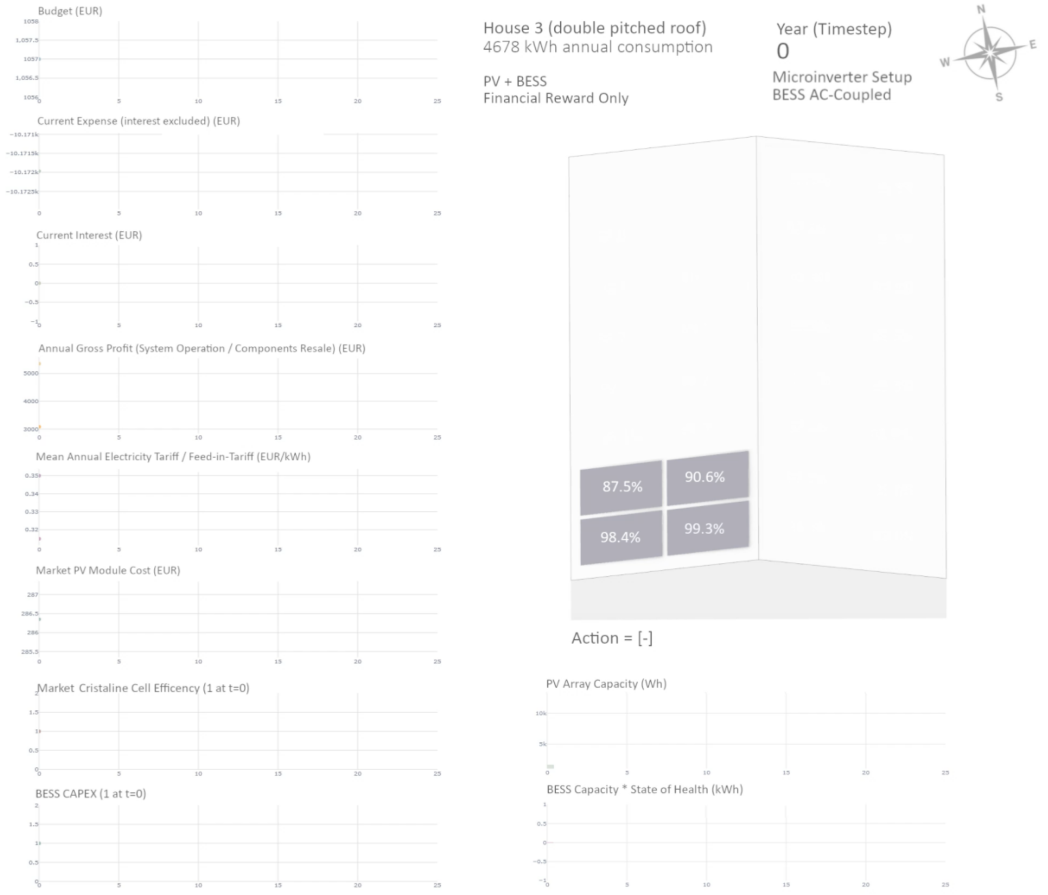
Evaluate on a separate test case

Test Different Algorithms and MARL

Broaden the Optimisation Scope
(other inverter configurations, building typologies)

Generalize over different environments


Budget (EUR)
Current Expense (interest excluded) (EUR)
Current Interest (EUR)
Annual Gross Profit (System Operation / Components Resale) (EUR)
Mean Annual Electricity Tariff / Feed-in-Tariff (EUR/kWh)
Market PV Module Cost (EUR)
Market Cristaline Cell Efficency (1 at t=0)
BESS CAPEX (1 at t=0)
House 3 (double pitched roof)
4678 kWh annual consumption
PV + BESS
Financial Reward Only
Year (Timestep)
0
Microinverter Setup
BESS AC-Coupled
N
E
S
W
86.8%
89.2%
91.6%
86.5%
87.9%
98.6%
92.7%
87.9%
Action = [-]
PV Array Capacity (Wh)
BESS Capacity * State of Health (kWh)


Budget (EUR)
Current Expense (interest excluded) (EUR)
Current Interest (EUR)
Annual Gross Profit (System Operation / Components Resale) (EUR)
Mean Annual Electricity Tariff / Feed-in-Tariff (EUR/kWh)
Market PV Module Cost (EUR)
Market Cristaline Cell Efficency (1 at t=0)
BESS CAPEX (1 at t=0)
House 3 (double pitched roof)
4678 kWh annual consumption
PV + BESS
Financial Reward Only
Year (Timestep)
0
Microinverter Setup
BESS AC-Coupled
N
E
S
W
87.5%
90.6%
98.4%
99.3%
Action = [-]
PV Array Capacity (Wh)
BESS Capacity * State of Health (kWh)

Thank You

- *GBM's analytic solution under Ito's interpretation*

$$S_t = S_0 \exp\left(\left(\mu - \frac{\sigma^2}{2}\right)t + \sigma W_t\right).$$

Expectation of Log Returns

$$E[\log(X_t) - \log(X_{t-1}) = \mu$$

Variance of Log Returns:

$$var[\log(X_t) - \log(X_{t-1})] = \sigma^2$$

- *OU's analytic solution under Ito's interpretation*

$$X_t = X_0 e^{-\lambda_t} + \mu(1 - e^{-\lambda_t}) + \sqrt{\frac{\sigma^2(1-e^{-2\lambda t})}{2\lambda} N(0,1)}$$

- *GBM with jump process analytic solution*

$$Panel(t) = Panel(0)exp\left[\left(\alpha - \frac{\sigma^2}{2} - \lambda_{PT}\theta\right)t + \sigma B_t\right] \times \prod_{i=1}^{N_t}(V_i)$$

- *Total radiation*

$$G_T = G_{h,b} \times \cos AOI + G_{h,d}\left(\frac{1+cos\theta_T}{2}\right) + G_{h,p}\left(\frac{1+cos\theta_T}{2}\right)$$

where:
$G_{h,b}$ is the direct beam radiation
$G_{h,d}$ is the diffuse horizontal radiation
$G_{h,p}$ is the reflected radiation
AOI is the angle of incident sunlight on a tilted plane
θ_T is the tilted angle of inclination relative to the ground surface

- *AOI between the Sun's rays and the PV array*

$$AOI = cos^{-1}(\cos\beta\ \cos(A-\varphi)\ sin\theta_T + sin\beta\ cos\,\theta_T)$$

where:
φ is the azimuthal deviation of the PV module
A is the sun azimuth angle
β is the sun altitude angle.

- *Cell Temperature*

$$T_c = T_{ambient} + \frac{\alpha \times G_T(1-\eta_m)}{U_c \times U_v \times WS}$$

where:
$T_{ambient}$ is the local ambient temperature,
$T_{c,STC}$ is the PV temperature under standard test conditions [25°C],
α is the PV cell absorption coefficient,
U_c is the heat loss factor coefficient dependent on the module construction,
U_v is the combined heat loss factor influenced by wind,
WS is the wind speed in m/s.