ETH zürich

Farmers and Biogas Plant Collective Dynamics: an Agent Based Model

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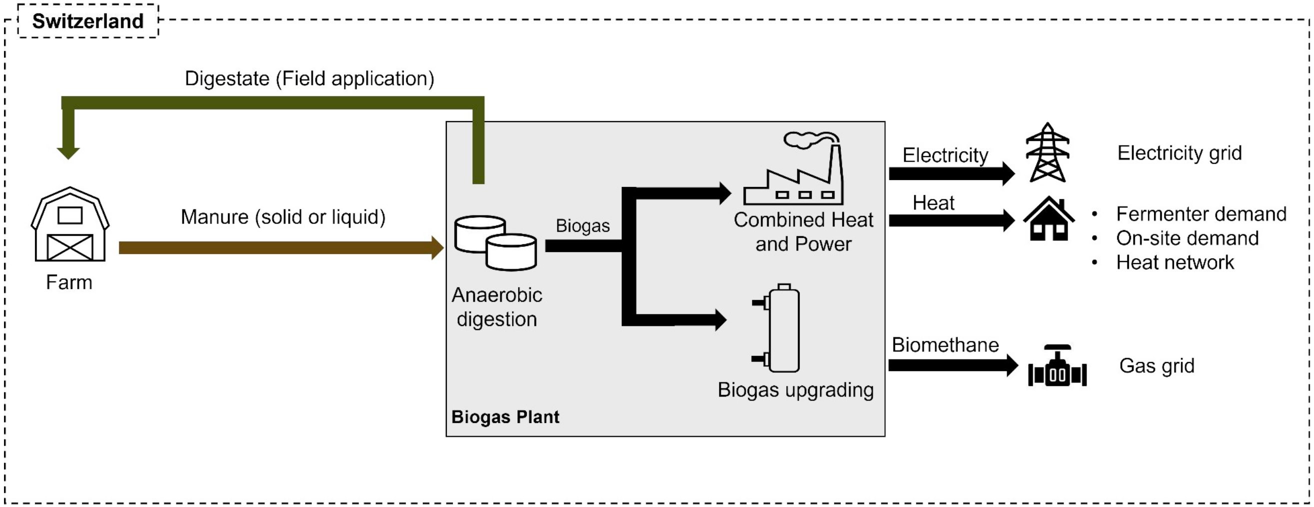
08.12.25

Introduction

Problem Statement

- Livestock produces considerable amount of manure ~24 million tonnes per year
- Currently, <5 % is used for energy → largely untapped potential
- Manure-to-energy pathways:



Problem Statement

Research Questions

RQ1: How do heterogeneous farmer preferences and collaboration mechanisms influence the emergence, adoption and size distribution of manure-to-energy installations in Switzerland?

RQ2: How do policy incentives (e.g., subsidy levels) and learning dynamics interact with collaboration mechanisms to influence the scale of biogas adoption?

Related Work

Related Work

- Farmer's willingness to adopt private and collective biogas facilities: An agent-based modeling approach (Burg et al. 2021) - analysis of current Swiss situation
    - Surveyed distribution of Swiss farmers, situations, and beliefs
    - ABM to match current Swiss plant distribution
    - Simulated economic factors (subsidies)

- Cooperation in manure-based biogas production networks: An agent-based modeling approach (Yazan et al. 2017) - ABM for Netherlands
    - Farmers and biogas producers separate agents
    - Interesting economic incentives due to legal regulations
        - Requirement to remove manure, more expensive during some months
    - Found distance to be very important factor

- Improving diffusion in agriculture: an agent-based model to find the predictors for efficient early adopters (Barbuto et al. 2019)
    - Closeness and clusterization most important in spreading early adoption

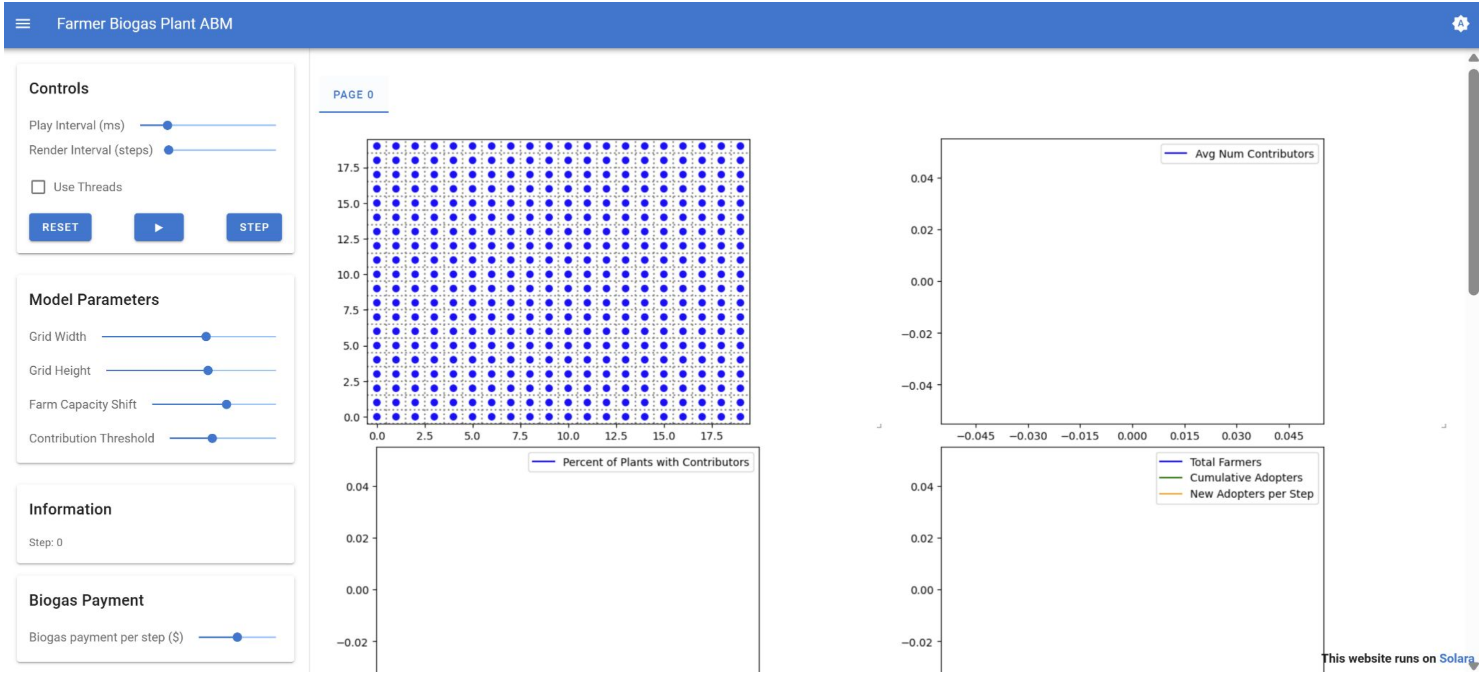
Model

Model basics & structure

- Grid of farmers (20×20 cells), each representing a livestock farm
- Two agent types:
  - Farmers: decide to build or contribute to a biogas plant
  - Biogas plants: created when farmers invest; different sizes and economies of scale
- Adoption influenced by:
  - Global learning (time-based awareness)
  - Social learning (adoption of neighbors)
  - Economic utility (NPV-based decision)
- Output metrics:
  - Number and size of plants, adoption timing, kW installed, contributors

Model basics & structure

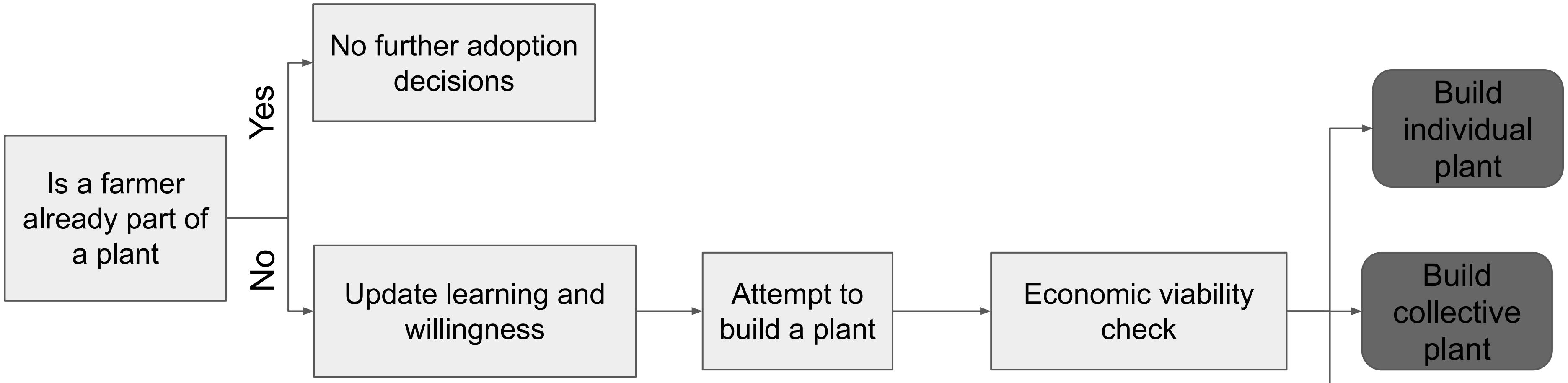
- Built using the Mesa Python framework for agent-based modeling
- Includes an interactive Solara interface for exploring model dynamics



Farmers

- Attributes
  - Livestock - sampled from Swiss distribution
  - Two willingness parameters - to build and contribute
    - "innovators" and "majority"
- Updates
  - Willingness - global and social
- Decisions
  - Build
  - Contribute

Decision logic of a farmer



- Apply global learning curve
- Compute social learning based on neighbors
- Update willingness to build and contribute

- Collective plant
- Individual plant

- Compute utility (NPV+co-owner penalties)
- Compare to minimum threshold

Learning mechanisms

Global learning (time-based):

- Modeled as a logistic S-curve
- k: learning_rate (steepness)
- t0: learning_midpoint

→ represents rising awareness and innovation diffusion

$$L(t) = \frac{1}{1 + e^{-k(t-t_0)}}$$

Social learning:

- Fraction of adopted neighbors in radius-2 neighborhood

→ represents learning from the local social environment

$$S = \frac{N_{\text{adopted}}}{N_{\text{neighbors}}}$$

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Willingness Equation:

For building: $$W_{\text{build}} = W^0_{\text{build}} + \alpha^{\text{build}}_{\text{social}} \cdot S + \alpha^{\text{build}}_{\text{global}} \cdot L(t)$$

For contribution: $$W_{\text{contribute}} = W^0_{\text{contribute}} + \alpha^{\text{contribute}}_{\text{social}} \cdot S + \alpha^{\text{contribute}}_{\text{global}} \cdot L(t)$$

- W^0 = baseline willingness
- α_{social} = weight_social_build / weight_social_contribute
- S = share of adopted neighbors
- $L(t)$ = global logistic learning curve

Economic utility function

- Net Present Value utility function
- Utility combines economic profitability and a penalty for co-ownership
- Higher utility leads to higher probability of adoption

Economic Component

1. Annual revenue

$$\text{Annual Revenue} = \text{kW} \times 24 \times 365 \times (\text{Stipend} + \text{Payment Shift})$$

2. Annual maintenance

$$\text{Annual Maintenance} = \frac{0.03 \times \text{CAPEX}}{\text{Maintenance Interval}}$$

3. Farmer's share of plant output

$$\text{Share}_i = \frac{\text{Farm Size}_i}{\text{Plant Capacity}}$$

4. Annual net profit for farmer

$$\pi_i = \text{Share}_i \times (\text{Annual Revenue} - \text{Annual Maintenance})$$

5. NPV

$$NPV_i = -\frac{\text{CAPEX}}{n_{\text{owners}}} + \sum_{t=1}^{T} \frac{\pi_i}{(1+r)^t}$$

6. Utility from profit (scaled)

$$U_{\text{profit}} = \frac{NPV_i}{\text{Profit Scale}_{CHF}}$$

Social Component

Each additional co-owner reduces utility

$$U_{\text{penalty}} = -\text{Co-Owner Penalty} \times (n_{\text{owners}} - 1)$$

Total Utility

$$U = U_{\text{profit}} + U_{\text{penalty}}$$

Adoption decision rule

Hard threshold

$$U < U_{\min} \;\Rightarrow\; \text{Do not build}$$

Probabilistic decision

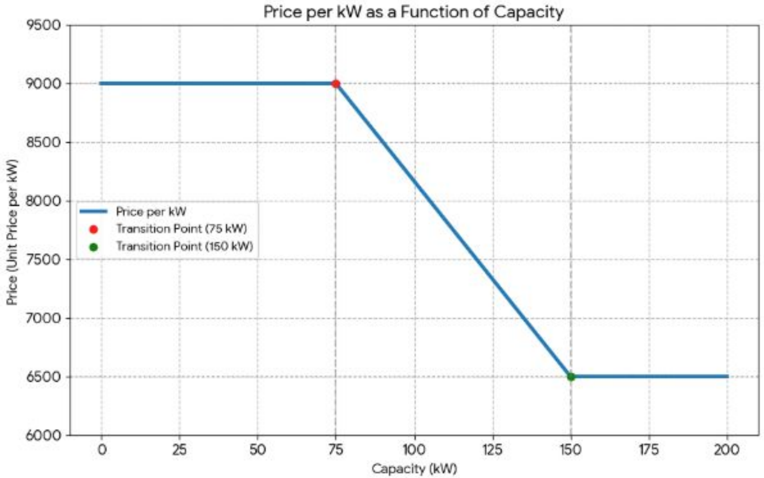
$$p_{\text{adopt}} = \frac{1}{1 + e^{-k \cdot U}}$$

Farmers adopt if

$$\text{random}() < p_{\text{adopt}}$$

Plant building and output

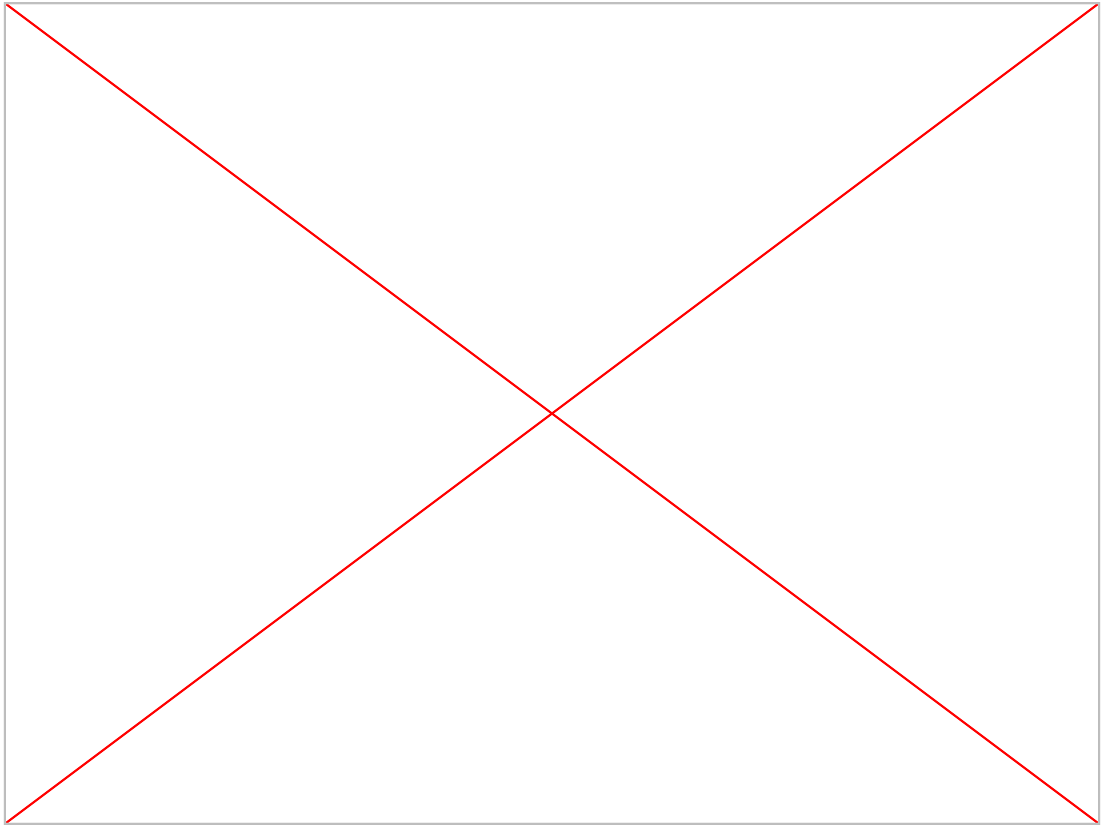
- Two parameters
  - Building cost
  - Efficiency (kW per substrate)
- Modeled using real-world cost and output estimates from Germany
  - Larger plant → decreasing $ / kW
  - Larger plant → increasing efficiency
- Use latest Swiss biogas subsidies
- Realistic capacity requirements and constraints



Plant building and output

- Simplifications - we don't model:
  - Physical (land) constraints
  - Operational labor overhead - generally considered minimal
  - Multiple owners - no data

Model output



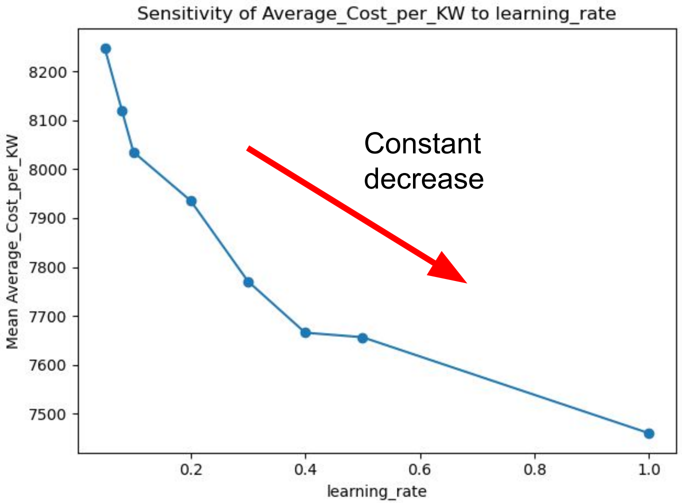
Performance Evaluation Metrics

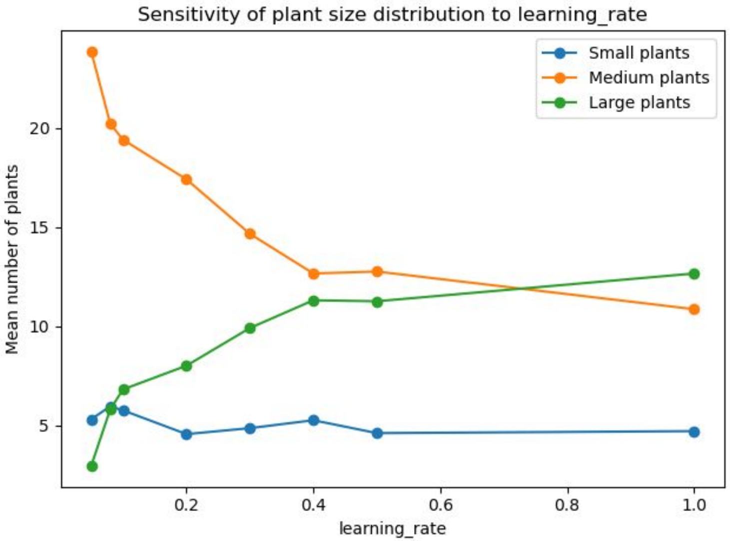
Calibration

- We match realistic Swiss distributions and pricing from [Burg et al., 2021]
  - Livestock distribution, plant costs and output, subsidies
- Calibrate on: resulting plant distribution
  - Fraction of individual vs. communal plants
  - Average number of contributors
- Calibration Parameters:
  - Willingness to build and contribute
  - Required utility
  - Co-owner penalty

Sensitivity analysis - Learning mechanisms

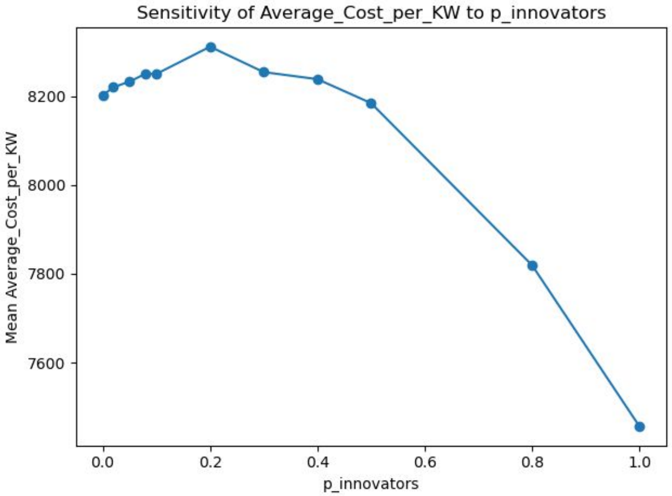
- Most parameters behave as expected
- Higher learning rates lead to higher adoption
- Earlier learning increases willingness and cooperation

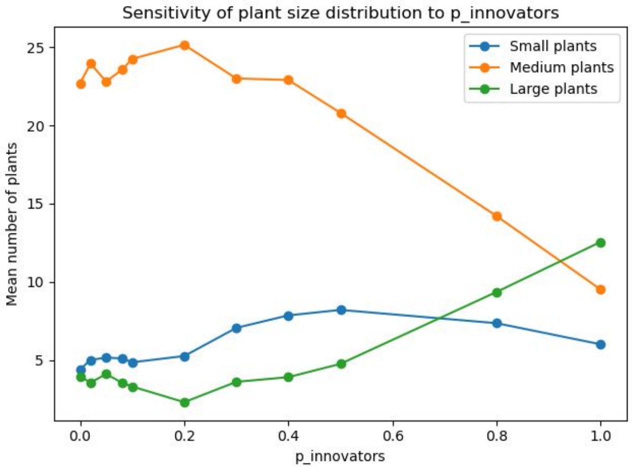




Sensitivity analysis - Learning mechanisms

Innovator share:



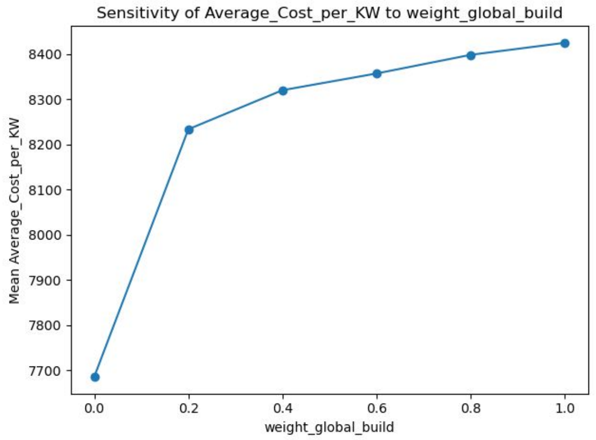


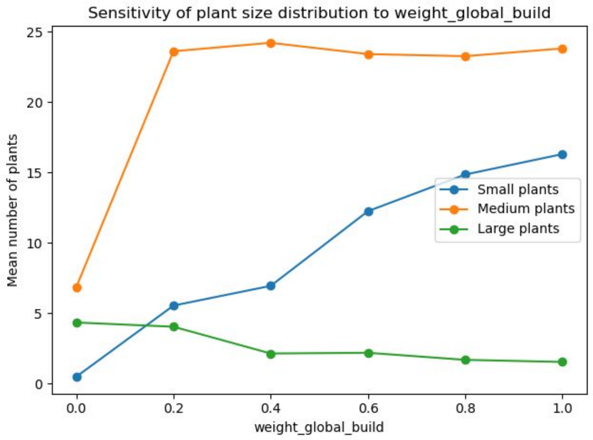
Expected: Higher innovator shares improve economic performance
Reality: Moderate innovator share (~20%) produces worst economic output
High innovator share triggers cooperation → shift to larger plants

Sensitivity analysis - Learning mechanisms

Global weight:

To build:





Expected: Increase adoption (more farmers build or contribute)

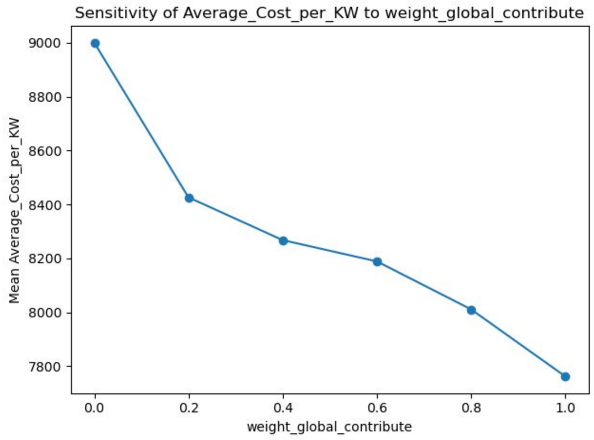
Reality: Adoption increases, but mostly through many individual plants

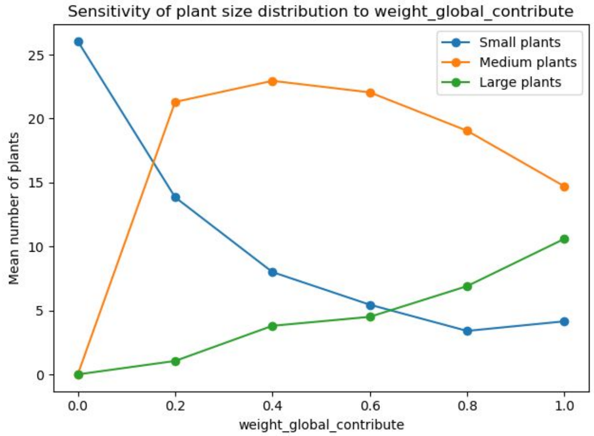
This leads to more installations, but not more efficient ones.

Sensitivity analysis - Learning mechanisms

Global weight:

To contribute:





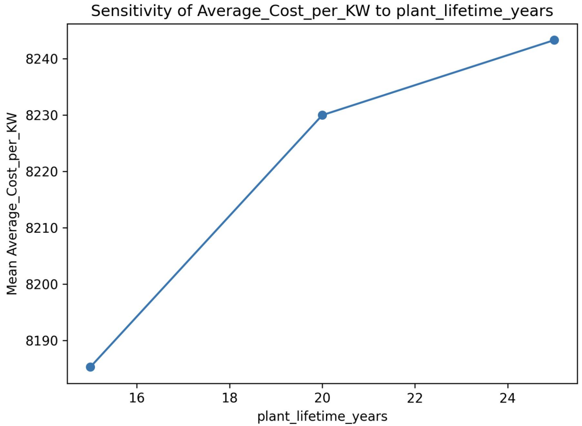
Expected: Increase adoption (more farmers build or contribute)
Reality: Strong global contribution weight increases cooperation
This leads to more large plants and lower costs

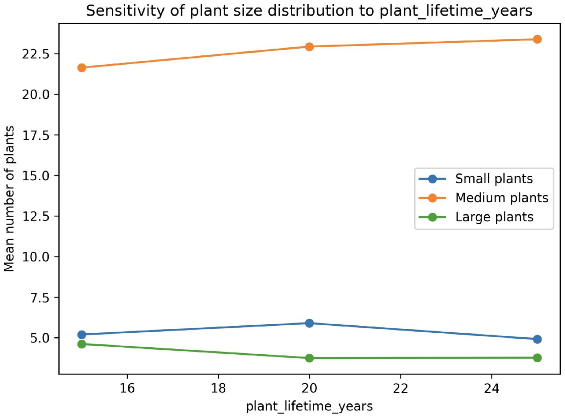
Trade-off

Individual motivation increases deployment, but collective motivation increases efficiency

Sensitivity analysis - Subsidy / Economic

- Mostly "expected"
  - Increasing farm capacity → more adopters and plants
  - Lower economic costs → more adopters and plants
  - Increasing subsidies → generally increases plants
- Insensitive parameters such as utility minimum threshold or plant lifetime

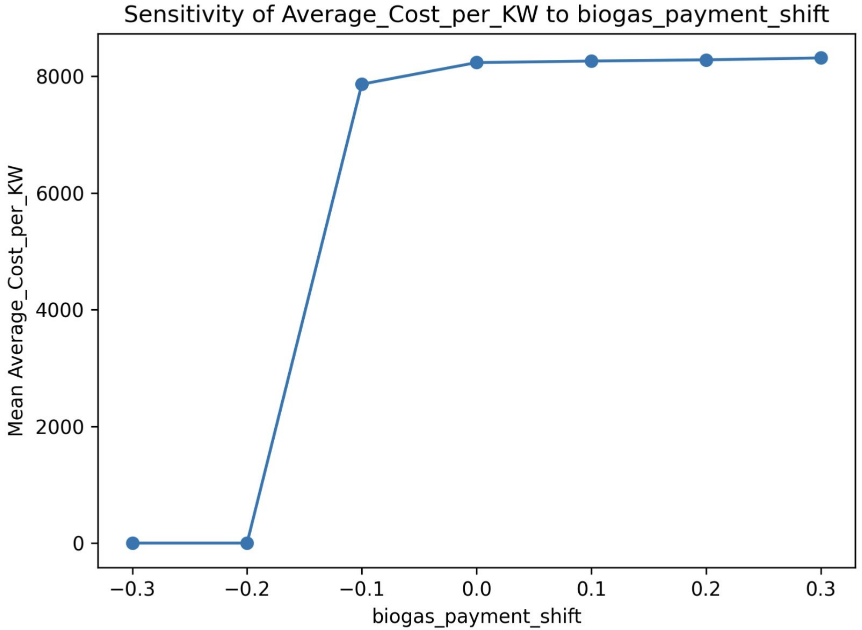


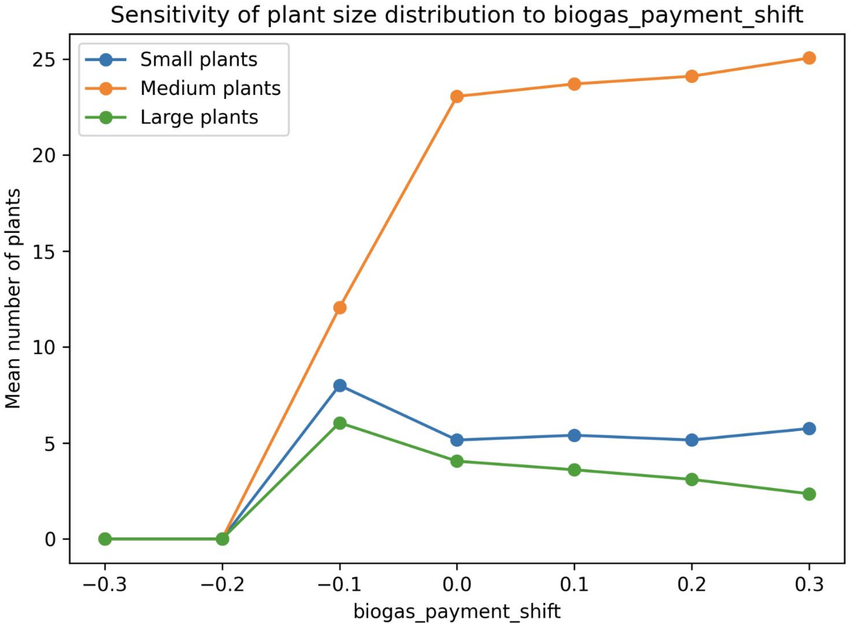


Limited influence on model output

Sensitivity analysis - Subsidy / Economic

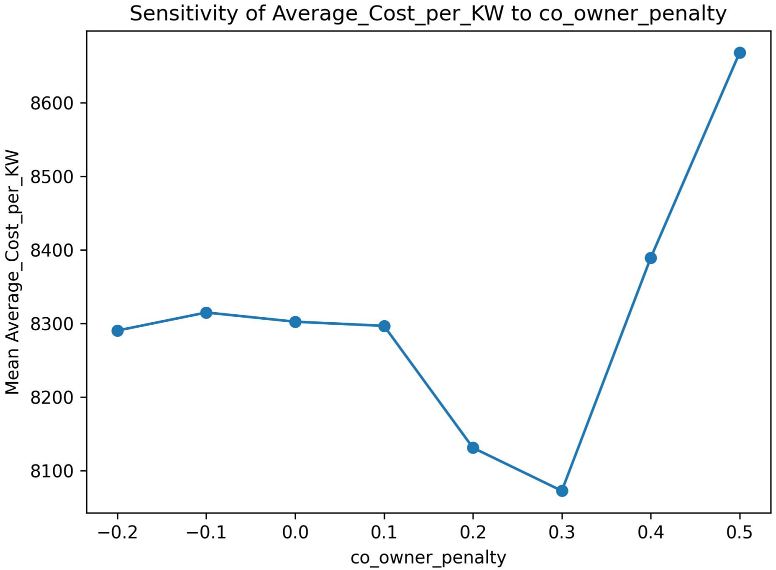
Biogas payment shift (subsidies)

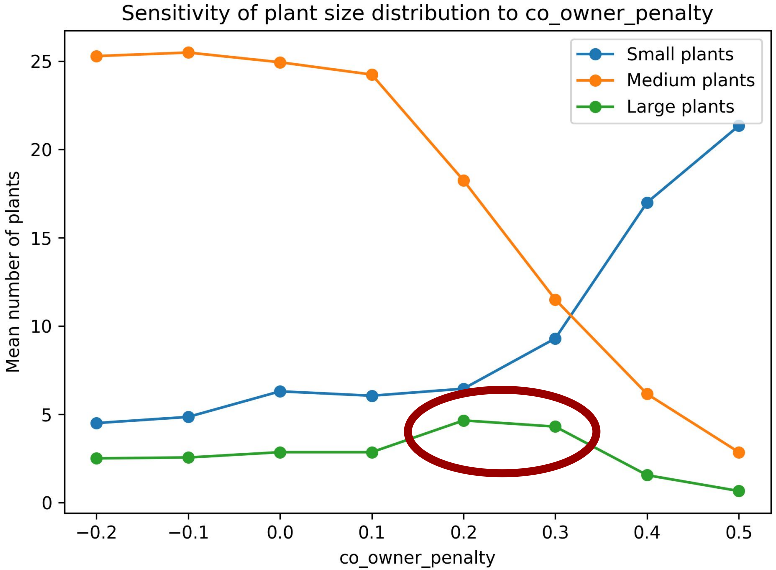




Sensitivity analysis - Subsidy / Economic

Unexpected - co-owner penalty - financial penalty on collaboration





Expected: more small plants -> higher costs
Reality: cheapest in middle

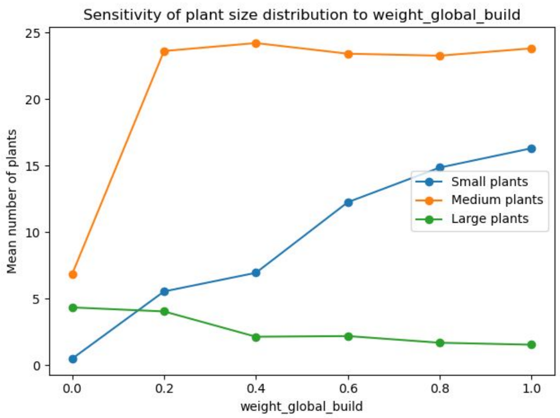
More large plants being built

Discussion & Conclusion

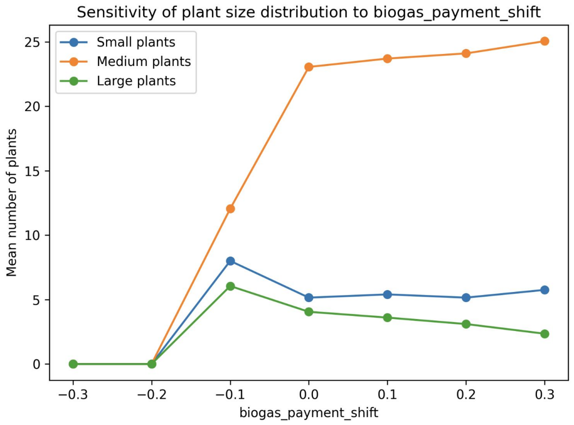
Discussion

RQ1: How do heterogeneous farmer preferences and collaboration mechanisms influence the emergence, adoption and size distribution of manure-to-energy installations in Switzerland?

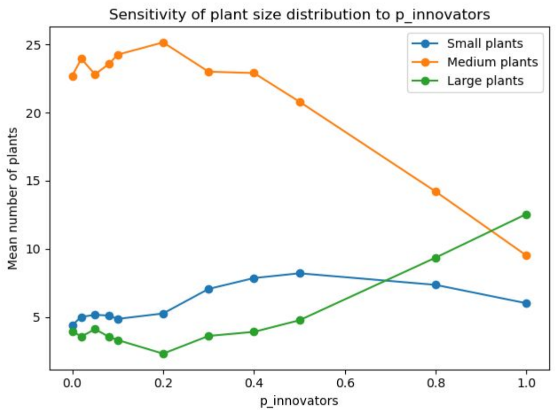
Answer: different "levers" have very different impacts on plant size distribution



Making farmers more likely to build increases small plants



Increasing subsidies increases medium plants

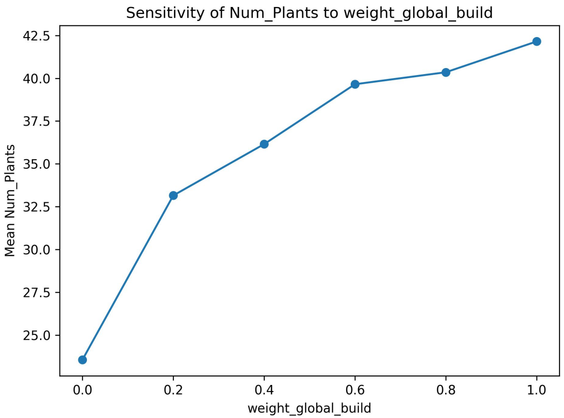


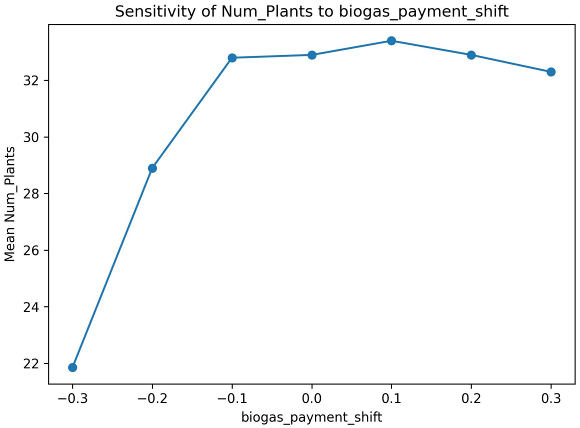
More innovation increases large plants

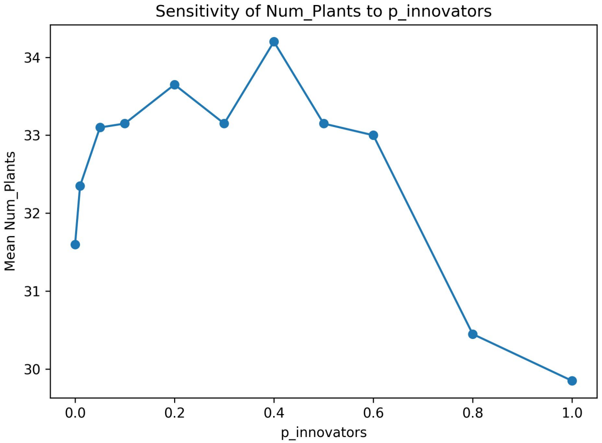
The question becomes: what outcome does Switzerland want?

Discussion

RQ2: How do policy incentives (e.g., subsidy levels) and learning dynamics interact with collaboration mechanisms to influence the scale of biogas adoption?







Similarly, we see that different incentives change the final number of plants.

Interestingly, for all these graphs, total final adopters remains relatively unchanged.

Conclusion

- Our model highlights how economic incentives, social learning and collaboration dynamics jointly shape biogas development
- Subsidies and willingness both raise adoption, yet the resulting plant sizes differ
- Possible conclusion - more worthwhile to spend money on advertising + knowledge sharing
- But - contingent on several assumptions:
  - Farmers can initially afford plants
  - Plants can be built anywhere
  - Subsidies stay in place forever
- It's complicated and depends on what Switzerland wants

Future Work

- Physical constraints - modeling actual topology, land constraints on building
  - Key factor in the Netherlands
- Multiple owner plants and associated willingness
- Economic modeling for contributors
  - Actual market dynamics
- Adoption speed

References

1. Vanessa Burg, Klaus G. Troitzsch, Deniz Akyol, Urs Baier, Stefanie Hellweg, Oliver Thees, Farmer's willingness to adopt private and collective biogas facilities: An agent-based modeling approach, Resources, Conservation and Recycling, Volume 167, 2021, 105400, ISSN 0921-3449, https://doi.org/10.1016/j.resconrec.2021.105400.

2. Devrim Murat Yazan, Luca Fraccascia, Martijn Mes, Henk Zijm, Cooperation in manure-based biogas production networks: An agent-based modeling approach, Applied Energy, Volume 212, 2018, Pages 820-833, ISSN 0306-2619, https://doi.org/10.1016/j.apenergy.2017.12.074.

3. Barbuto, A., Lopolito, A. & Santeramo, F.G. Improving diffusion in agriculture: an agent-based model to find the predictors for efficient early adopters. Agric Econ 7, 1 (2019). https://doi.org/10.1186/s40100-019-0121-0

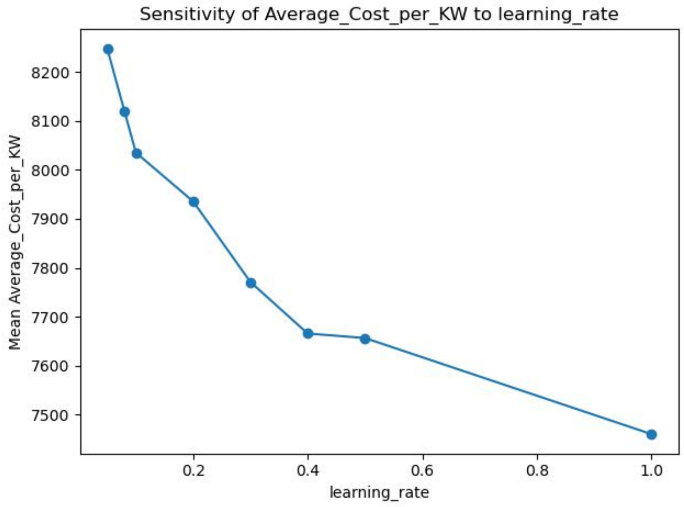
4. Djatkov, Djordje & Viskovic, Miodrag & Martinov, Milan & Nesterovic, Aleksandar & Bojic, Savo & Effenberger, Mathias & Venus, Thomas J.. (2021). Small biogas plants. 10.13140/RG.2.2.20644.40321.

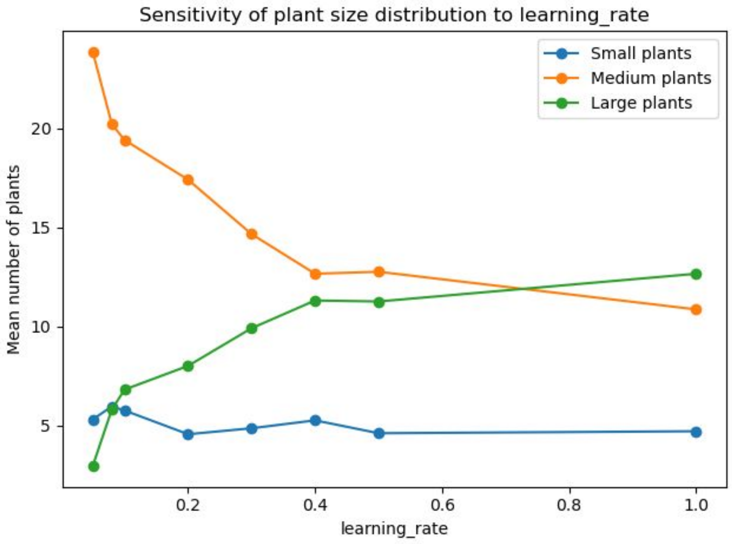
5.https://www.dvl.org/uploads/tx_ttproducts/datasheet/DVL-Publikation-Schriftenreihe-22_Vom_Landschaftspflegematerial_zum_Biogas-ein_Beratungsordner.pdf

Appendix

Sensitivity analysis - Learning mechanisms

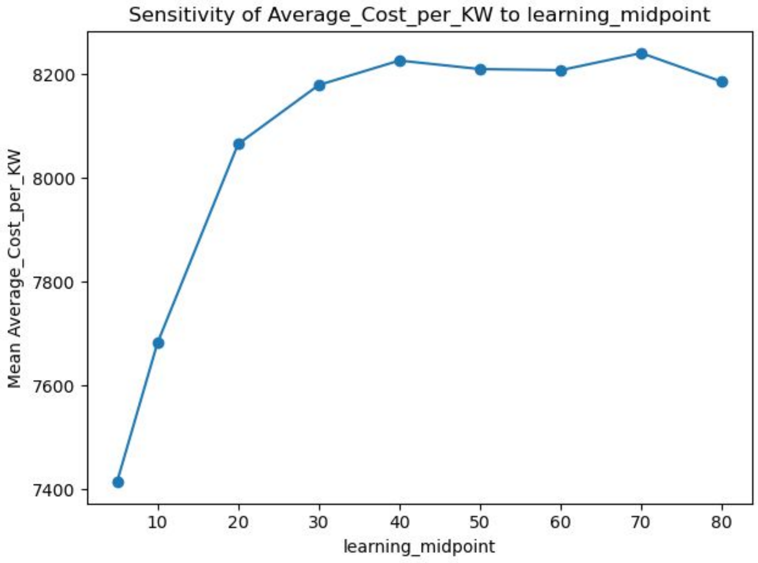
Learning rate:

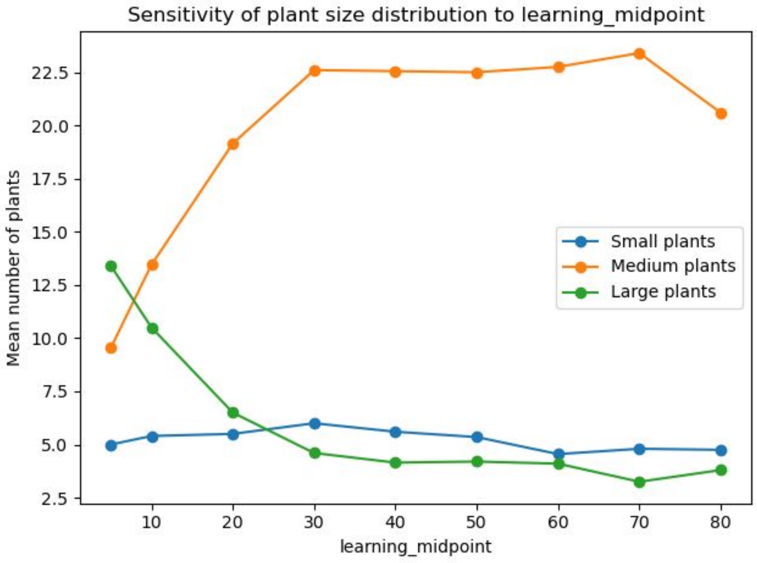




Sensitivity analysis - Learning mechanisms

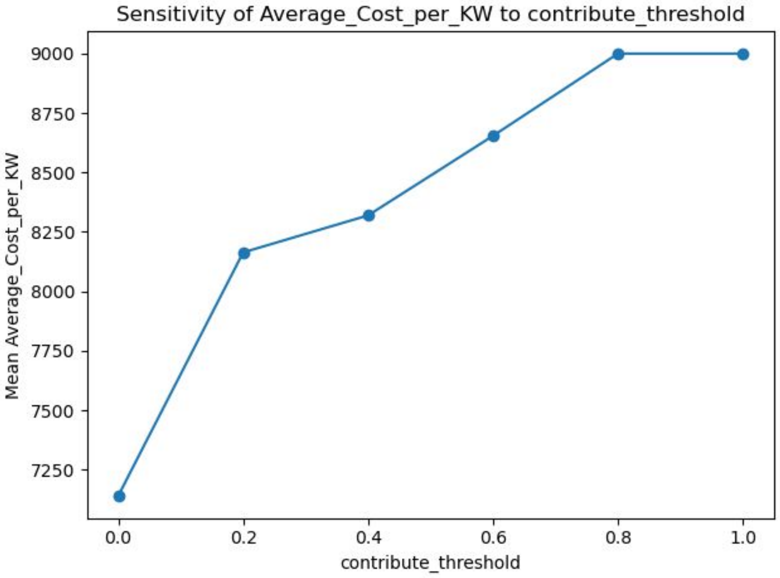
Learning midpoint:

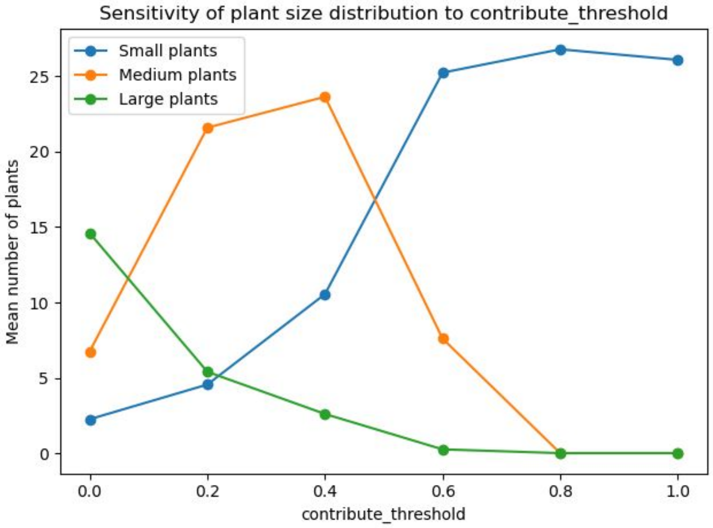




Sensitivity analysis - Learning mechanisms

Contribute threshold:

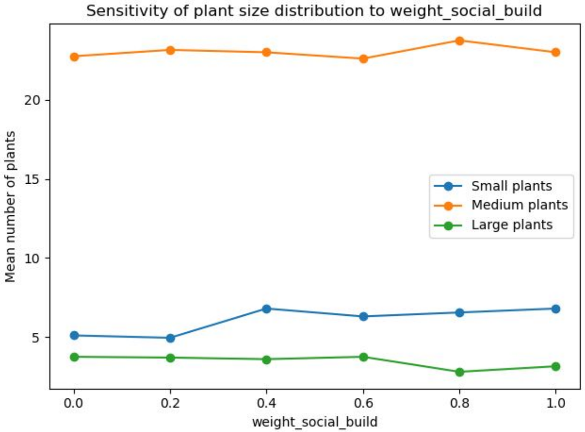




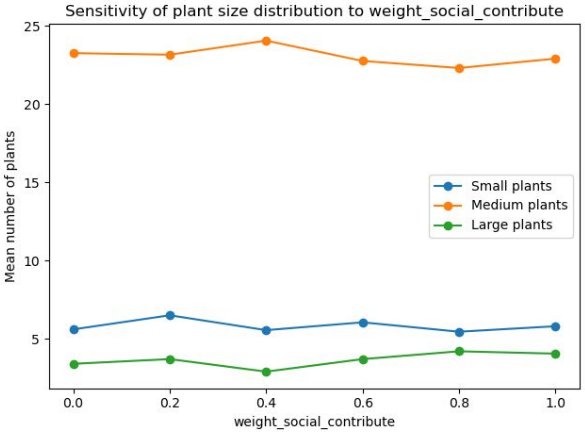
Sensitivity analysis

Social weight:

To build:



To contribute:



Expected: Social learning should increase adoption

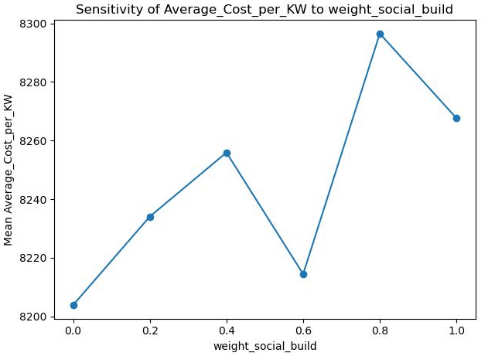
Reality: Social weights show very limited influence on plant size outcomes

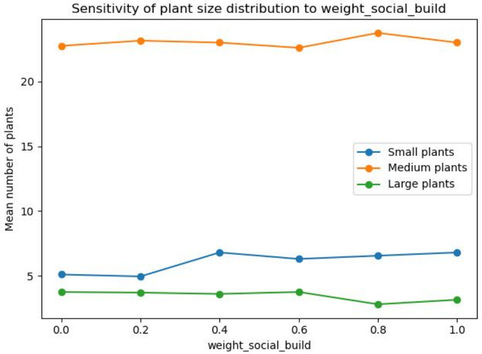
Adoption patterns remain almost unchanged across the parameter range

Sensitivity analysis

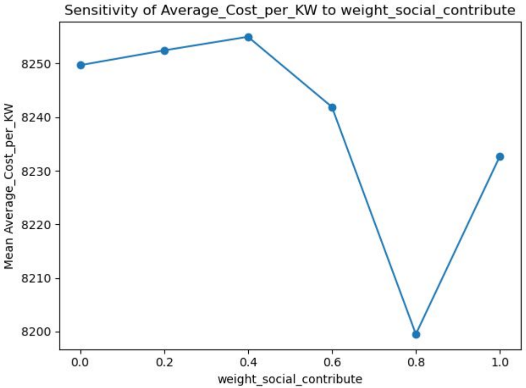
Social weight:

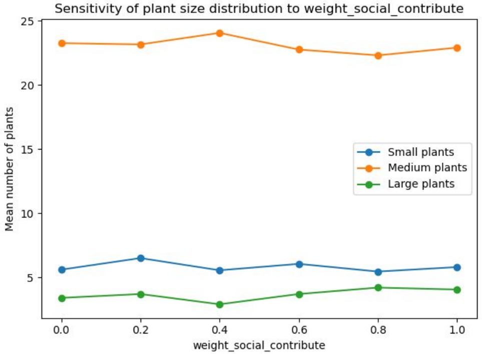
To build:





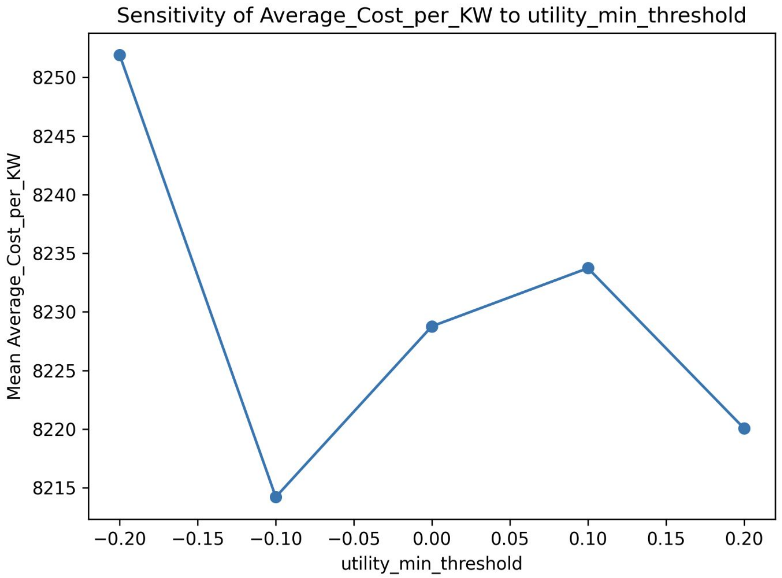
To contribute:

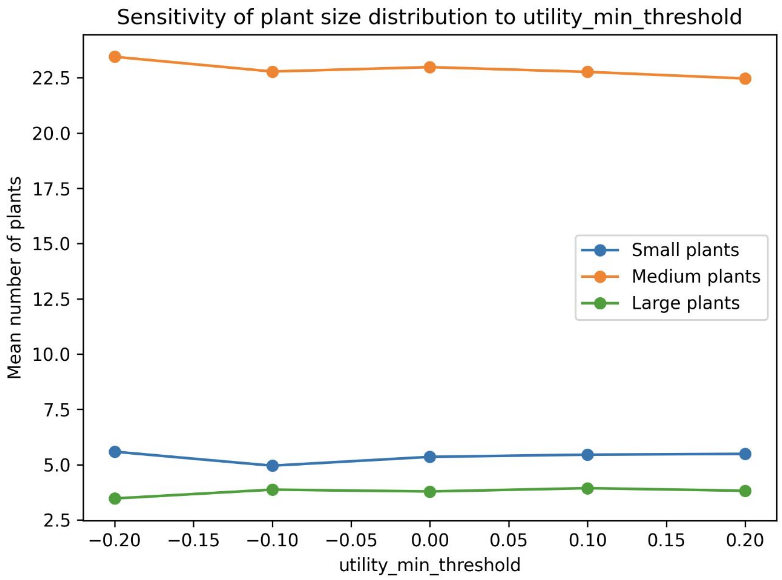




Sensitivity analysis

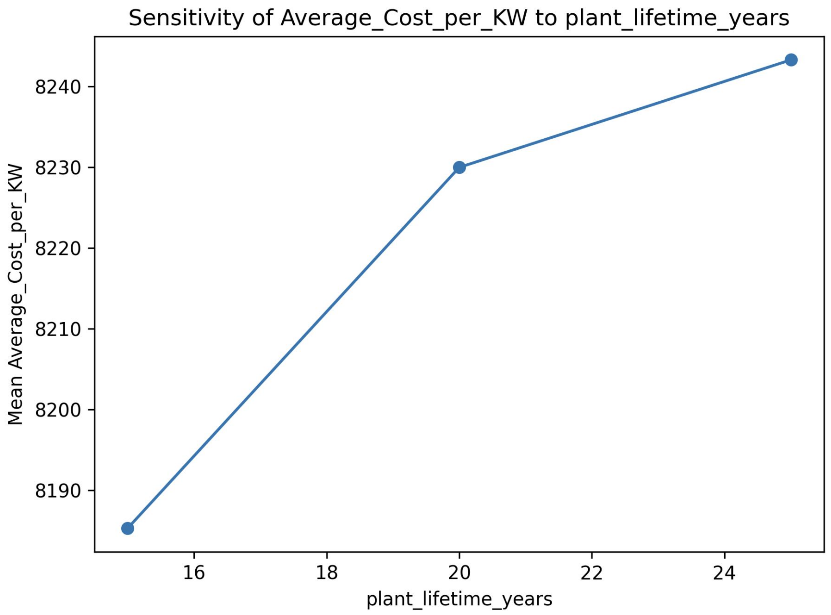
Utility minimum threshold

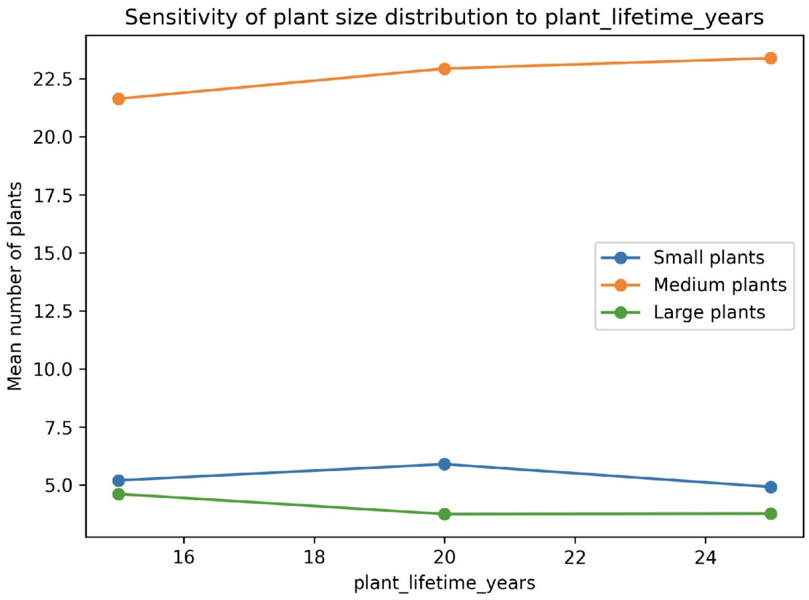




Sensitivity analysis

Plant lifetime years





Projects (continued)

Suggested presentation structure:

1. **Introduction:** research question clearly stated
2. **Related Work:** students briefly discuss related work and state-of-the-art approaches
3. **Model(s):** explanation and relation to the phenomenon under investigation.
4. **Performance evaluation metrics:** chosen by the students and motivated appropriately.
5. **Summary, discussion, conclusions and outlook** (possible future work)

Please approach us in case of any questions.

Grading

Presentation ca. 30 min + Q&A 10min (may change depending on number of presentations) 100 points

- Objective/research question – 10
- Related work – 10
- Model Quality – 40
- Model and Result analysis – 40

Deadline 2

- Deadline for slides: 01.12.2025 at 16:00 CET
- Deadline for final git-repo (use the same repo for both slides and code): 22.12.2025 at 23:59 CET
  - Submission link
    - https://forms.gle/pvuPz83S9qJ8Bcn58