Simulating Rooftop Solar Panel Adoption: An Agent-Based Model of Household Decision-Making in Amsterdam

Caroline Christandi Loe[1] and Erkinai Derkenbaeva[1,2]

[1]Wageningen University and Research, Wageningen, The Netherlands
[2] Amsterdam Institute for Advanced Metropolitan Solutions, Amsterdam, The Netherlands
caroline.christandiloe@wur.nl

Abstract. This abstract outline ongoing research using the Solar-SIMS Agent-Based Model (ABM) to explore rooftop solar panel adoption in Amsterdam. The model simulates household decision-making using the HUMAT framework, integrating cognitive dissonance, descriptive and injunctive social norms, and financial feasibility. Solar-SIMS captures complex social and economic dynamics that influence solar adoption, emphasizing the role of peer influence and policy interventions. Running from 2023 to 2030, the model provides insights into adoption patterns at the neighborhood level, revealing disparities across socio-economic groups and evaluating different policy scenarios. Expected results include empirical observations of spatial and temporal adoption patterns, offering policy recommendations for promoting equitable energy transitions.

Keywords: Agent-Based Model (ABM), Rooftop Solar Panels, HUMAT Framework, Energy Transition, Social Influence, Energy Equity, Cognitive Modeling.

1 Introduction

The shift towards renewable energy is essential for tackling the global climate crisis. Cities are pivotal in this change, with rooftop solar energy providing an accessible and scalable solution. Amsterdam aims for a 55% reduction in CO_2 emissions by 2030 and climate neutrality by 2050 (City of Amsterdam, 2020). Rooftop solar panels are a key part of this strategy, given the city's significant solar potential—estimated at over 6.9 PJ annually, enough to supply nearly 50% of its electricity demand [1]. However, adoption patterns reveal that solar panels remain predominantly accessible to wealthier households, leaving low- and middle-income families underserved [2]. This disparity is visible in neighborhoods across the city, where clusters of solar panels on affluent homes contrast sharply with the rooftops of less privileged areas. This not only limits Amsterdam's ability to meet its climate goals but also exacerbates energy inequality, underscoring the need for a comprehensive model that addresses the social, economic, and cognitive dynamics influencing adoption [3, 4]. Several agent-based models

(ABMs) have explored social influence, socio-economic disparities, and cognitive factors in household energy transitions [5–8]. These models highlight how adoption behaviors are shaped by both social and spatial factors [9].

The Solar-SIMS agent-based model (ABM) simulates household decision-making for adopting rooftop solar in a conceptual neighborhood layer. Here, 'neighborhood' denotes spatial proximity—households observe nearby rooftops and are influenced by visible solar installations [8, 10] . This spatial approach enhances social network dynamics, highlighting how observable adoption influences behavior. This spatial perspective emphasizes how observable adoption shapes behavior in conjunction with social network dynamics. Solar-SIMS captures how individual decisions evolve under the influence of social networks, cognitive dissonance, and policy interventions, offering insights into neighborhood-level adoption patterns from 2023 to 2030. By identifying the social and economic factors that drive adoption, Solar-SIMS supports the design of more equitable energy policies [11].

Through the framework, households evaluate and update their decision-making based on satisfaction across three motives. When their motives conflict, agents experience cognitive dissonance, which drives them to reduce this tension by interacting with peers or adjusting their behavior. In this context, cognitive dissonance refers to the psychological discomfort agents experience when their actions (e.g., not adopting solar panels) conflict with their values or social expectations (e.g., wanting to be environmentally conscious or keep up with neighbors) [8, 12].

2 Conceptual Framework

Solar-SIMS applies the HUMAT framework, which draws upon the established Cognitive Dissonance Theory, Social Contagion Theory, Theory of Planned Behavior (TPB) and diffusion of innovations theory [4, 13, 14]. Agents are embedded in a social network that captures both spatial and social influences. Spatial neighbors are conceptually defined as nearby rooftops that agents can observe within a defined radius. Although the model does not explicitly embed GIS-based data from Amsterdam districts, it simulates how visible solar installations are in the immediate surroundings. On the other hand, social peers represent individuals with whom agents interact directly, thus connecting to others within their network.

HUMAT agents main assessment is their satisfaction through three main motives: experiential (financial feasibility), social (peer influence), and values-based (environmental awareness), which guide their decision to adopt rooftop solar panels. The experiential motive pertains to financial feasibility, emphasizing income, subsidies, and the agent's capability to invest in solar panels. The value-based motive reflects environmental consciousness and the inclination to act according to personal environmental ethics and a sense of duty. Both of these motives are static. Lastly, the social motive is influenced by dynamic social interactions with spatial neighbors and peers, where descriptive norms emerge from observing others' adoption behaviors, and direct social pressures shape injunctive norms.

When these motives are not aligned, agents experience a conflict between their motives and actions; they seek to reduce this internal tension by adjusting their perceptions, modifying their behavior, or interacting with their social network for validation and information [8]. This tension can arise from social dilemmas (peer pressure or unmet social needs) or non-social dilemmas (financial constraints or misalignment with environmental values). For instance, an agent with strong environmental awareness yet facing financial limitations might feel cognitive dissonance upon seeing neighbors widely adopting solar energy. This situation can create conflicting motivations and result in delayed decisions. On the other hand, a robust blend of social and values-driven motivations may offset financial barriers, promoting adoption even in the face of economic difficulties.

Additionally, social influence is critical in the model, shaping adoption decisions through descriptive and injunctive norms [14, 15]. Descriptive norms influence households by passively observing solar adoption trends in their surrounding agents, while injunctive norms arise from direct peer interactions that create social pressure to conform. Solar-SIMS agents are embedded in a social network, which consists of neighbors and peers who influence decision-making in distinct ways [4]. Spatial neighbors are defined by physical proximity, influencing others primarily through descriptive norms, where visible solar installations in the neighborhood indicate what is typical and desirable. This influence grows as more neighbors adopt solar panels, reinforcing an agent's perception of solar adoption as a social norm. On the other hand, peers represent individuals with whom the agents communicate (friends or colleagues). They influence agents through injunctive norms, exerting direct social pressure to conform [4, 9]. Unlike passive observation, personal recommendations and validation from peers which often have a more substantial impact on individual decisions [2, 13].

At the conceptual level, the interaction between social norms and agents' evolving motives creates feedback loops that lead to emergent neighborhood-level adoption patterns [16]. These patterns provide insights into the clustering of adoption behavior and the conditions under which adoption spreads more rapidly [4, 5]. Solar-SIMS explores how these motives interact and evolve, revealing adoption patterns across neighborhoods and socio-economic groups. The framework highlights key behavioral dynamics often overlooked in traditional models by focusing on the interaction between social influence, financial capacity, and environmental values. These patterns offer valuable insights for policymakers designing targeted interventions to promote equitable and widespread adoption.

3 Process Overview

This section explains a high-level description of the key processes and sequence of actions in Solar-SIMS, focusing on agent behaviors, interactions, and the key steps of the simulation. Fig 1. shows how an agent makes decisions. It all starts with initializing and evaluating motives. Next, the agent checks whether adoption is feasible by considering whether the roof is suitable, whether there are any building regulations to follow, and who owns the property. Finally, the agent either decides to adopt or waits and re-visits the decision later.

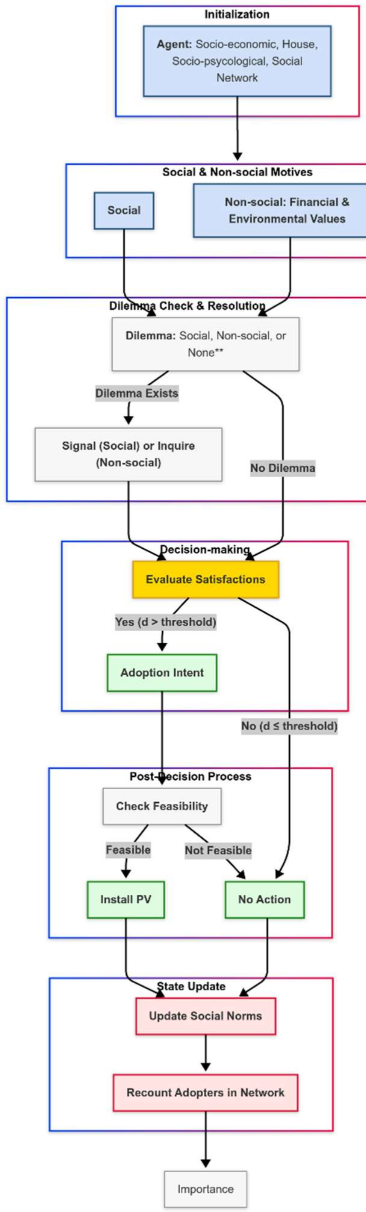

Fig. 1. Conceptual Flowchart of Solar-SIMS Decision-Making.

This flowchart outlines the decision-making steps in Solar-SIMS, focusing on five stages: initialization, motive evaluation, dilemma resolution, adoption intent, and post-decision updates. During initialization, agents are characterized by socio-economic, socio-psychological, house-related, and social network attributes. Socio-economic traits include income, education (linked to environmental awareness), migration background, and house ownership. Socio-psychological traits reflect environmental awareness, the importance of motives, and social norm perceptions. House characteristics, such as roof suitability, building regulations, and building type, determine adoption feasibility. Social network attributes capture the size and strength of influence from peers and neighbors. Agents evaluate satisfaction in experiential, social, and values-based motives while assessing adoption feasibility. If cognitive dissonance arises, agents resolve it by adjusting perceptions or interacting with peers. Post-decision updates create feedback loops that influence future decisions and shape neighborhood-level adoption patterns over time.

3.1 Overview of Agent Behavior

Solar-SIMS simulates household agents' decision-making on rooftop solar adoption over 28 quarterly time steps from 2023 to 2030. Each agent represents a household in an Amsterdam neighborhood with distinct attributes (e.g., income, environmental awareness, social network connections) and decision motives (experiential, social, and values-based).

Agent behavior is shaped by internal motives, external social influences, and policy interventions, which interact dynamically over time to drive decision-making. First, internal motives, including financial feasibility (experiential motive) and environmental values (values-based motive). These motives reflect agents' long-term characteristics—financial capacity and personal commitment to sustainability. For example, agents with high environmental awareness are more likely to adopt, provided they have sufficient financial resources [2, 5]. Second, social influences are through descriptive norms (observation of nearby solar installations) and injunctive norms (direct interactions with social peers, such as friends or colleagues). The strength of social influence depends on the credibility and similarity of peers [2, 6, 9]. Lastly, policy interventions, like economic incentives and communication campaigns, can modify agents' financial feasibility or enhance their social awareness. These factors interact during each decision cycle, resulting in dynamic shifts in agent behavior and higher level patterns.

3.2 Stepwise Process

The agent decision-making process in Solar-SIMS follows a stepwise sequence, as illustrated in Fig 1. Each timestep consists of several key stages: initialization and motive evaluation, cognitive dissonance check, adoption feasibility check, and post-decision updates. The process begins with initialization and motive evaluation, during which agents update their attributes and evaluate their satisfaction with experiential, social, and values-based motives. These updated motives reflect the agent's internal preferences and external circumstances.

At each time step, cognitive dissonance may arise from conflicting motivations regarding adoption; agents seek resolution by interacting with a social peer from their network. They then re-evaluate their motives for adoption using an importance-weighted sum, where each weight signifies its significance in the agent's decision-making. If overall satisfaction exceeds the adoption threshold, the agent assesses feasibility before installing solar panels. Lastly, agents must pass a technical feasibility check to meet key external adoption conditions if they choose to adopt. First, the household's ownership status is confirmed—only homeowners are eligible to proceed with adoption. Additionally, the roof's suitability is evaluated against criteria such as adequate space, optimal orientation, and structural integrity to support solar panel installation. Finally, agents must comply with local building regulations, which may restrict installations in areas with heritage protections or specific limits. If any of these feasibility criteria are not met, agents must delay their adoption decision to a later time step.

The final step is the post-decision update, where agents adjust their satisfaction levels and perceptions of social norms based on their evaluations. These updates create feedback loops that reinforce social norms and promote future adoption within the neighborhood. Over time, this process drives the emergence of neighborhood-level adoption patterns, revealing clusters of rapid adoption and highlighting the socio-economic factors influencing solar adoption rates. [6].

4 Model Calibration and Sensitivity Analysis

Calibration and sensitivity analysis are essential in ensuring the validity, robustness, and reliability of Solar-SIMS model outcomes. These processes refine agent behaviors, verify the accuracy of adoption patterns, and identify key parameters that influence model dynamics. Calibration will rely on real-world data from the WoON Dutch survey (2021), which provides population attributes of Amsterdam. This ensures that the initial agent population accurately represents the diversity of households in Amsterdam districts and building characteristics (data on roof suitability, ownership status, and building type). We will adjust the model until it closely aligns with the real-world data regarding how many people adopted solar panels in each district, when they adopted them, and where they were located. Sensitivity analysis will be carried out to evaluate the robustness of the model outcomes. Key parameters will be systematically varied to assess their impact on adoption patterns, neighborhood-level clustering in social network models, policy effects, and decision-making thresholds. Additional parameters, such as agent heterogeneity, policy duration, and time lag in decision-making, will help identify critical conditions under which adoption accelerates or stagnates. This comprehensive analysis will illustrate the robustness of model outcomes and highlight the key drivers of adoption, ensuring that simulation results remain consistent across multiple scenarios [7, 8].

5 Expected Results

Solar-SIMS is expected to generate insights into the spatial and temporal patterns of rooftop solar adoption at the neighborhood level, revealing how social influence, financial capacity, and policy interventions shape adoption decisions. Solar-SIMS is expected to generate insights into rooftop solar adoption's spatial and temporal patterns, revealing how neighborhood effects and reinforcing social norms drive clustering behavior. The model will illustrate conditions under which spatial clusters of adoption emerge, creating areas of high adoption while leaving others underserved. The model will also reveal adoption temporal dynamics, specifically how it accelerates after reaching tipping points to see the strength of descriptive and injunctive norms.

Policy scenario simulations will assess how targeted interventions, such as financial incentives or communication campaigns, affect adoption outcomes [9, 17]. For example, increasing subsidies or focusing communication on neighborhoods with low adoption could trigger tipping points, boosting adoption and reducing spatial disparities. The results will help identify leverages for system transformation, tipping points and the most effective combinations of policies to encourage equitable adoption and maximize solar potential [18].

The model is expected to highlight significant socio-economic disparities in adoption patterns as previous studies have shown [2, 7]. While wealthier households are more likely to adopt early due to their greater financial capacity, low- and middle-income households may experience delays or remain excluded, even with high environmental awareness. This disparity highlights the need for targeted policy interventions, such as subsidies and communication campaigns, to reduce adoption gaps and ensure a fair energy transition [7].

Unlike traditional economic models, Solar-SIMS emphasizes the role of social influence and cognitive processes, providing a more comprehensive understanding of adoption dynamics through the HUMAT cognitive framework while also focusing on social influence. The model's conceptual framework is based on real-world data, which makes it highly relevant for policymakers. Moreover, the framework can be adapted to other urban contexts, enabling comparative studies across cities with different socio-economic and regulatory environments. Lastly, Solar-SIMS contributes to the growing field of energy justice by exploring the intersection of technology adoption and social equity.

Disclosure of Interests. This study was conducted as part of the MSc program at Wageningen University, and the authors have no competing interests to declare that are relevant to the content of this article.

6 References

1. AMS Institute: Amsterdam could meet nearly half its electricity needs by better utilizing its rooftops, https://www.ams-institute.org/news/amsterdam-could-meet-nearly-half-its-electricity-needs-by-better-utilizing-its-rooftops/, last accessed 2025/01/29.

2. Wolske, K.S., Gillingham, K.T., Schultz, P.W.: Peer influence on household energy behaviours. Nat Energy. 5, 202–212 (2020). https://doi.org/10.1038/s41560-019-0541-9.
3. Moglia, M., Nygaard, C.A., Glackin, S., Cook, S., Tapsuwan, S.: Hybrid Approach for Modelling the Uptake of Residential Solar PV Systems, with Case Study Application in Melbourne, Australia. JASSS. 25, 2 (2022). https://doi.org/10.18564/jasss.4921.
4. Antosz, P., Jager, W., Polhill, G., Salt, D., Alonso-Betanzos, A., Sánchez-Maroño, N., Guijarro-Berdiñas, B., Rodríguez, A.: Simulation model of social innovation: Deliverable 7.2. European Union (2019).
5. Rai, V., Henry, A.D.: Agent-based modelling of consumer energy choices. Nature Clim Change. 6, 556–562 (2016). https://doi.org/10.1038/nclimate2967.
6. Rai, V., Robinson, S.A.: Agent-based modeling of energy technology adoption: Empirical integration of social, behavioral, economic, and environmental factors. Environmental Modelling & Software. 70, 163–177 (2015). https://doi.org/10.1016/j.envsoft.2015.04.014.
7. Derkenbaeva, E., Hofstede, G.J., Van Leeuwen, E., Halleck Vega, S., Wolfers, J.: ENERGY Pro: Spatially explicit agent-based model on achieving positive energy districts. MethodsX. 12, 102779 (2024). https://doi.org/10.1016/j.mex.2024.102779.
8. Antosz, P., Jager, W., Polhill, G., Salt, D., Scalco, A., Alonso-Betanzos, A., Sánchez-Maroño, N., Guijarro-Berdiñas, B., Rodríguez, A.: SMARTEES: D7.3 Simulation implementations. European Union (2020).
9. Curtius, H.C., Hille, S.L., Berger, C., Hahnel, U.J.J., Wüstenhagen, R.: Shotgun or snowball approach? Accelerating the diffusion of rooftop solar photovoltaics through peer effects and social norms. Energy Policy. 118, 596–602 (2018). https://doi.org/10.1016/j.enpol.2018.04.005.
10. Mundaca, L., Samahita, M.: What drives home solar PV uptake? Subsidies, peer effects and visibility in Sweden. Energy Research & Social Science. 60, 101319 (2020). https://doi.org/10.1016/j.erss.2019.101319.
11. Sundaram, A., Gonçalves, J., Ghorbani, A., Verma, T.: Network dynamics of solar PV adoption: Reconsidering flat tax-credits and influencer seeding for inclusive renewable energy access in Albany county, New York. Energy Research & Social Science. 112, 103518 (2024). https://doi.org/10.1016/j.erss.2024.103518.
12. Li, K., Liang, H., Kou, G., Dong, Y.: Opinion dynamics model based on the cognitive dissonance: An agent-based simulation. Information Fusion. 56, 1–14 (2020). https://doi.org/10.1016/j.inffus.2019.09.006.
13. Rogers, E.M.: Diffusion of innovations. Free Press, New York London Toronto Sydney (2003).
14. Jager, W., Guijarro-Berdiñas, B., Bouman, L., Antosz, P., Alonso Betanzos, A., Salt, D., Polhill, J.G., Rodríguez Arias, A., Sánchez-Maroño, N.: Simulating the Role of Norms in Processes of Social Innovation: Three Case Studies. JASSS. 27, 6 (2024). https://doi.org/10.18564/jasss.5168.
15. Cialdini, R.B., Kallgren, C.A., Reno, R.R.: A Focus Theory of Normative Conduct: A Theoretical Refinement and Reevaluation of the Role of Norms in Human Behavior. In: Advances in Experimental Social Psychology. pp. 201–234. Elsevier (1991). https://doi.org/10.1016/S0065-2601(08)60330-5.

16. Akhatova, A., Kranzl, L., Schipfer, F., Heendeniya, C.B.: Agent-Based Modelling of Urban District Energy System Decarbonisation—A Systematic Literature Review. Energies. 15, 554 (2022). https://doi.org/10.3390/en15020554.
17. Derkenbaeva, E., Hofstede, G.J., Van Leeuwen, E., Halleck Vega, S.: Simulating households' energy transition in Amsterdam: An agent-based modeling approach. Energy Conversion and Management. 294, 117566 (2023). https://doi.org/10.1016/j.enconman.2023.117566.
18. City of Amsterdam: Amsterdam Climate Neutral 2050: New Amsterdam Climate Roadmap, https://www.amsterdam.nl/en/policy/sustainability/policy-climate-neutrality/, (2020).