***GIS-Integrated Agent-Based Modeling of Residential Solar PV Diffusion***

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**Overview**

Adoption of new technologies in a population occurs cumulatively over time, producing positive feedback through networks.[1](#_ENREF_1) As a result, large-scale diffusion trends *emerge* out of consumer decision-making at the household-level, and involve *complex interactions* among the consumers and other actors in the system.

The Theory of Planned Behavior (TPB) hypothesizes that the behavior of individuals is driven by their behavioral intention, which in turn is determined by the individual's attitude towards the behavior, subjective norms (perceived social pressure), and perceived behavioral control.[2](#_ENREF_2),[3](#_ENREF_3) For new technologies that involve significant upfront costs and informational uncertainties, a key mechanism through which individuals update their attitudes and beliefs about subjective norms involves “word of mouth” and other forms of peer effects.[4](#_ENREF_4),[5](#_ENREF_5) *Peer effects* within social networks of individuals have recently been confirmed as playing a significant role in the adoption of solar photovoltaic (PV) systems in the residential sector.[6](#_ENREF_6),[7](#_ENREF_7)

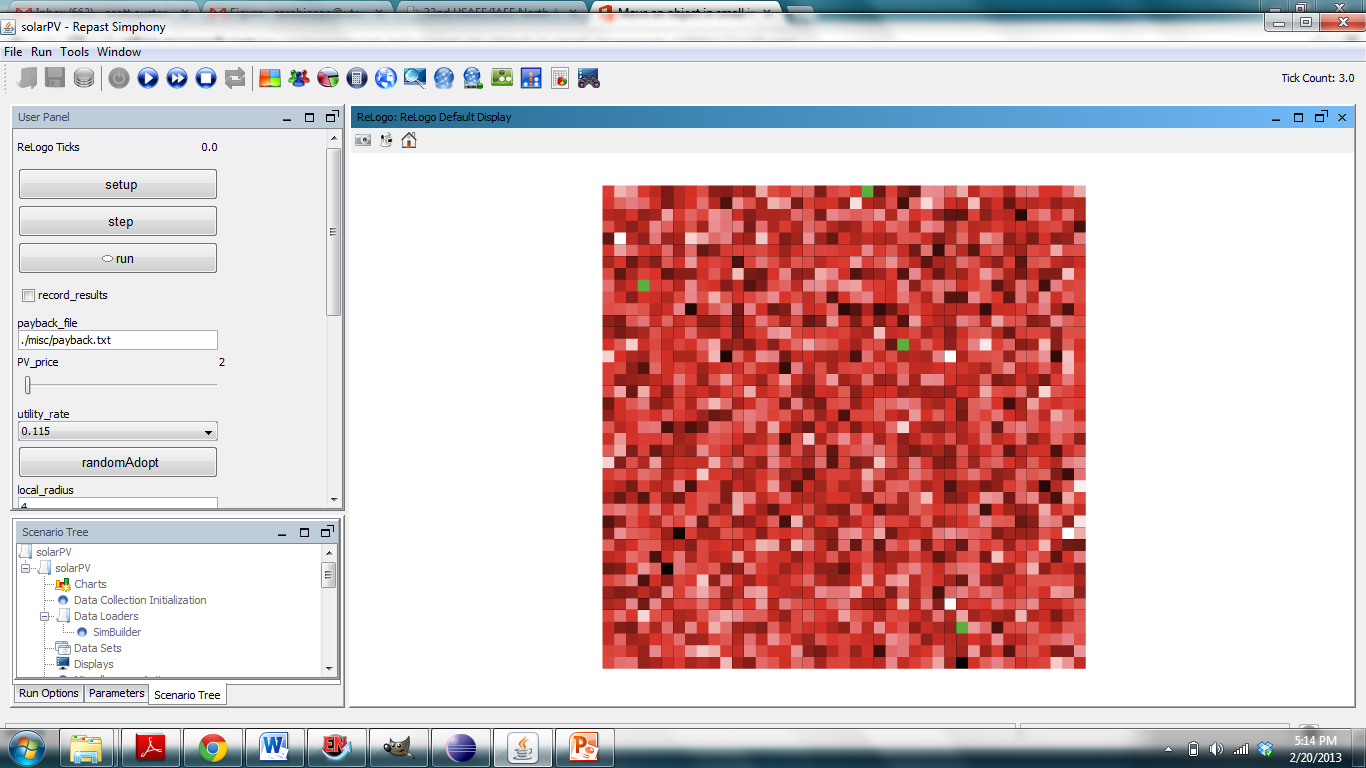
In this paper we use an agent-based model (ABM) integrated geospatially with ArcGIS 10 to simulate the diffusion of residential PV in Austin, Texas. This simulation serves two functions: 1) to test hypotheses regarding consumer behavior and associated network interactions within the context of the residential PV sector; and 2) to forecast adoption scenarios within the study-area to inform incentive structures, identify future markets, and better integrate PV in the electric grid.

**Data and Methodology**

From spring 2005 to summer 2012, the City of Austin area, encompassing more than 200,000 households, has had over 1750 households install PV systems, representing a compound annual growth rate (CAGR) of 35.6%. To allow for a highly granular representation of agent networks using real-world locational information (see below), in this paper we focus on one zip code within the Austin area. Our subsample involves the interaction of nearly 7,700 agents (households). Future work will extend this analysis to simultaneously simulate interactions of agents in all zip-codes in the Austin area.

Household-level data was obtained from four distinct data streams: 1) solar program data on rebate recipients’ system cost, size, and date of installation; 2) the Travis Central Appraisal District parcel land use type, market value, associated geographic coordinates; 3) a survey of Texas solar PV owners, described in detail in Rai and McAndrews[8](#_ENREF_8); and 4) individualelectricity consumption, utility rates, and PV system electricity generation with time-of-day and monthly variations.[9](#_ENREF_9) Information from all data streams were joined in a GIS of residential households within the study area. This allows for a high degree of fidelity when calculating individual agent decision thresholds, social networks, and threshold values in the ABM.

The structure of agent interactions is represented by small world networks.[10](#_ENREF_10) The small world function defines the network of an agent probabilistically—in the model 90% of connections between agents were established within a proximity-bounded neighbors set, and 10% were established randomly (Figure 1). Further, we treat agent intention to adopt PV as a dynamic variable, altered by the relative agreement function[11](#_ENREF_11) within the agent’s small world network. Thus, agent networks are utilized within the relative agreement function to allow for the dynamic exchange of information between agents based on the degree of overlap in their intentions. In order to assess the level of actual behavioral control,[3](#_ENREF_3) agents make financial calculations based on payback period. If the payback period is found to be within the agent’s tolerance threshold, the agent adopts PV.



**Figure 1**: Illustration of the geo-referenced agent-based model. Traditional grid ABMs (left) misrepresent agent geography and result in unrealistic social networks and agent interactions. Agents exchange opinions (shown in red-scale) via a relative agreement function within their small world social network (shown here for one agent).

**Results and Conclusions**

Simulated diffusion patterns demonstrate significant clustering or spatial autocorrelation (p < 0.001), with neighborhoods of high-density adoption as well as areas of low or zero adoption. This result is driven by the small world networks with geometrically contiguous neighbors and illustrates the local nature of peer effects, fitting with earlier descriptions in the literature.6,[7](#_ENREF_7),[12](#_ENREF_12) Initial forecasts suggest that through 2020, adoption levels in Austin will remain well within the “early adopters” category as defined by Rogers.[1](#_ENREF_1) Interestingly, as the simulated time-frame increases the level of clustering tends to decrease, creating a more dispersed pattern of diffusion. The model is highly sensitive to initial adoption rates, demonstrating the influence of early adopters on the actual patterns of technology diffusion that ultimately emerge.

Previous work has noted the importance of peer effects in the diffusion of residential PV and shown how this effect operates in the pre-purchase search period.6,7 Using two specific theoretical representations of the components of consumer interaction processes—small world networks for the structure and relative agreement model as the mechanism—we demonstrate that such complex interactions help explain real-world empirical properties. The Diffusion of Innovations theory posits the importance of innovators and early adopters,1 which this research confirms, but we also note the importance of “high value agents” defined by their ability to bridge neighborhoods through strong extra-local connections. Future work will expand the geographical area to include all households in Austin and test the effects of "extremists" in the population,[13](#_ENREF_13) of different network structures, and of the hierarchical importance of initial attitudes in the population.[2](#_ENREF_2)

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