Up-scaling Agent-Based Discrete-Choice Transportation Models using Artificial Neural Networks

Lance E. Besaw[1], Donna M. Rizzo[1], Margaret J. Eppstein[2], Michael B. Pellon[2], David K. Grover[1], Jeffrey S. Marshall[1]

[1]School of Engineering
[2]Department of Computer Science
University of Vermont, Burlington, VT

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Motivation

- Regulatory actions by federal, state and local governments can play a critical role in influencing the transportation energy market
  - Consumer tax rebates, government subsidies, publically available charging stations, energy prices (fuel and electricity), among others
- We have developed an agent-based model (ABM) to simulate vehicle purchasing behavior for PHEV market penetration modeling

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Model and Data Description

- Complexities of the city-scale discrete-choice model have been presented previously (Pellon *et al., 2009*)
- City-scale, agent-based, discrete-choice model with social influence and basic economics
  - Prius vs. Prius-like PHEV
  - Conformity - Our physical and social neighbors influence our decision to consider/purchase a new technology (Axelrod, 1997)
  - Threshold model – certain number of neighbors must possess a PHEV before agent considers/purchases one (Watts 2002)
  - Heterogeneous agents (ages, salary, social network size, social susceptibility, greenness, etc) are distributed in space
  - Grounded with data (NHTS, EIA, U. of Michigan & Reuters) where available and basic assumptions

Resarch Question

- Can we use an artificial neural network to learn the behavior of the city-scale, discrete-choice, agent-based model with social influence?
  - Replicate ABM linear and non-linear dynamics
  - Capture effects of social interactions

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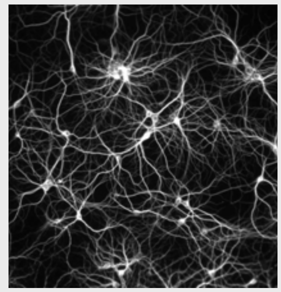
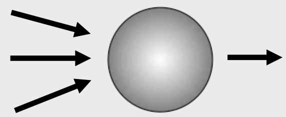
Artificial Neural Networks (ANNs)

- Pattern recognition algorithms modeled after the human brain
- Non-parametric, parallel, statistical methods
- Data-driven (learn inherent relationships)
  - More data → better predictions
  - Multiple data types
- Used on problems where traditional methods are unfeasible
- Handwriting & speech recognition, stock market prediction, ...



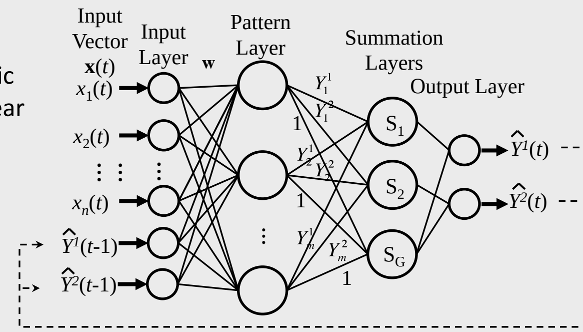


ANN Algorithms

- There are as many different ANNs as there are traditional statistical methods
- Unsupervised
  – Self-organizing map developed by Kohonen (1989)
- Supervised
  – Maps non-linear relationships between predictor and response variables (Hayken 1998)
  – Feedforward backpropagation
    - Most popular ANN in literature
    - Learning is based on gradient descent
    - Stochastic in nature – can get stuck in local minima, can be over trained, can suffer from lengthy training time

Generalized Regression Neural Network

- Specht, 1991
- Nonlinear, non-parametric extension of multiple linear regression
- Order of polynomial not defined *a priori*
- Single pass training
- Optimize smoothing parameter



$$D_i^2 = (\mathbf{w}_i - \mathbf{x})^{\mathrm{T}} (\mathbf{w}_i - \mathbf{x})$$

$$\hat{Y}^1 = \frac{\sum_{i=1}^{n} Y_i^1 \exp\left(-\frac{D_i^2}{2\sigma^2}\right)}{\sum_{i=1}^{n} \exp\left(-\frac{D_i^2}{2\sigma^2}\right)}$$

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ABM Simulations

- 4,320 different model simulations with varying model parameters
  - Total population of 1,000 agents
- Train GRNN on 3,000 random simulations (~80% of total)
- Validate and test GRNN on 1,320 simulations
  - Select only a few for demonstration
- Pertinent parameters
  - Size of social network networks
  - Social susceptibility (assumed)
  - Annual income, driving distribution (NHTS)
  - How far into the future do agents consider economic benefits (if at all)
  - Projected gas prices (EIA)
  - PHEV price premium (hymotion.com)

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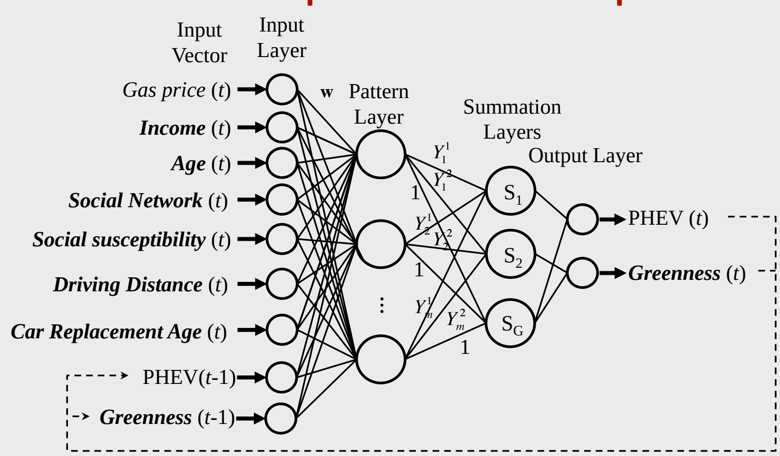
GRNN Inputs and Outputs



Bold designates distributions

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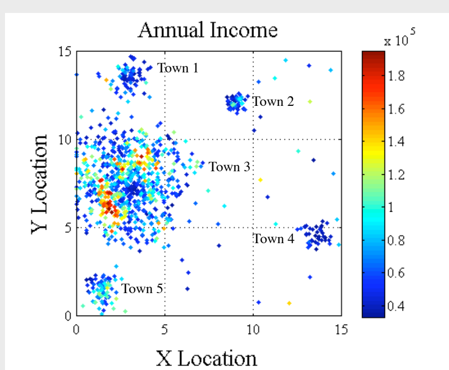
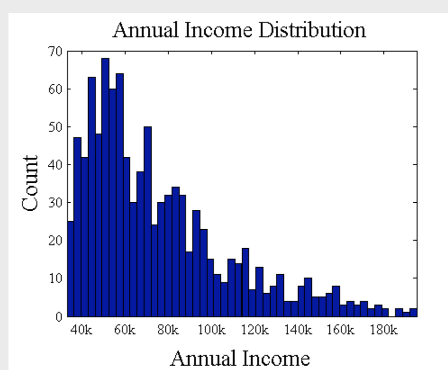
Annual Income





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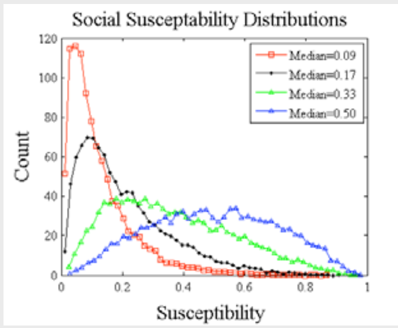
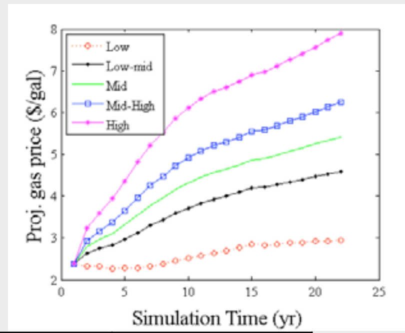
Example Model Input Data





Model Parameter	Training & Validation Dataset	Prediction Dataset
Median Social Susceptibility	[0.01, 0.09, 0.33, 0.49]	[0.17, 0.45]
Proj. Gas Price	Low, Medium, High	Low-mid, Mid-High
PHEV Price Premium	$5k, $10k, $15k	$7k, $13k
Town Identification	1, 2, 3, 4, 5	1, 2, 3, 4, 5
Region Population	1,000	1,000

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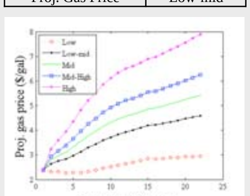
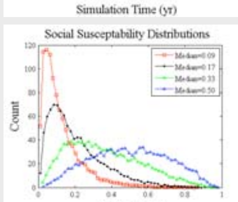
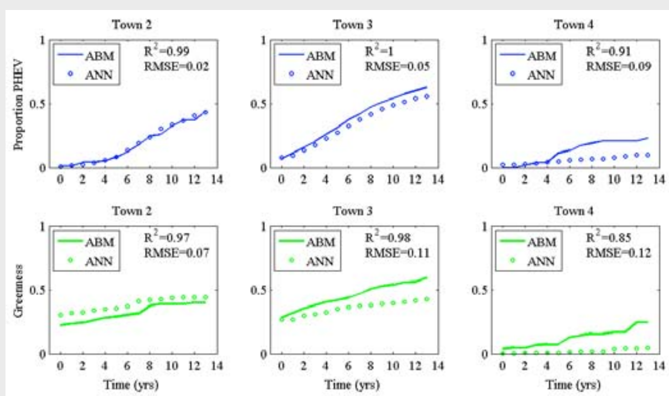
Simulation 1 – Low Social Susceptibility

Parameter	Scenario 1
PHEV premium	$13k
Social Susceptibility Median	*0.17*
Proj. Gas Price	Low-mid







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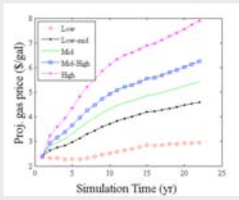
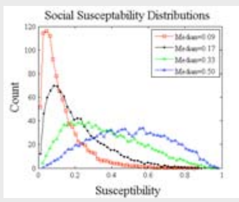
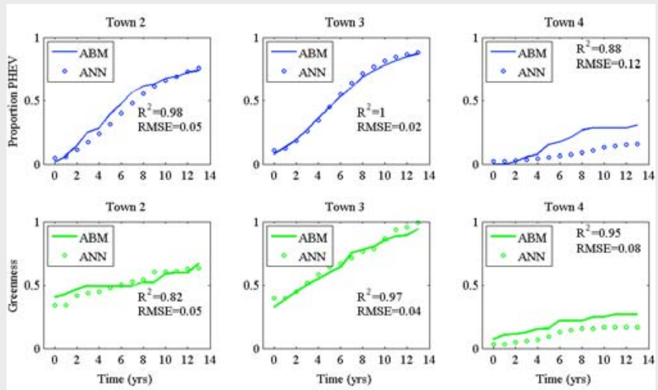
Simulation 2 – High Social Susceptibility

Parameter	Scenario 2
PHEV premium	$13k
Social Susceptibility Median	*0.45*
Proj. Gas Price	Low-mid







ANN Validation and Prediction Results

Variable	Dataset	Statistic	Town 1	Town 2	Town 3	Town 4	Town 5	All Towns
Number of Agents	Validation & Prediction	Mean	74	66	726	55	79	1,000
PHEV-Fleet Proportion	Validation	Mean R^2	0.89	0.83	0.88	0.57	0.83	0.8
		Std. Dev. R^2	0.22	0.34	0.24	0.33	0.25	0.28
	Prediction	Mean R^2	0.97	0.98	0.99	0.94	0.96	0.97
		Std. Dev. R^2	0.02	0.01	0.01	0.03	0.02	0.02
Greenness	Validation	Mean R^2	0.85	0.82	0.87	0.47	0.76	0.75
		Std. Dev. R^2	0.27	0.31	0.24	0.29	0.29	0.28
	Prediction	Mean R^2	0.83	0.74	0.97	0.89	0.91	0.87
		Std. Dev. R^2	0.09	0.06	0.01	0.04	0.01	0.04

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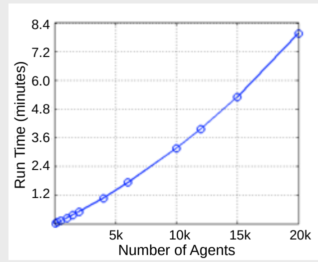
Computational Speedup

- The ABM scales super linearly with increasing number of agents.
  – Large amount of computation performed at every time step for every agent (*e.g.,* threshold to consider purchasing a PHEV based on social and geographic networks)
  – Generation of 4,320 simulations: ~24 hrs



- GRNN took ~4 hours to train (3,000 simulations) and ~9 minutes to predict all 1,320 simulations (0.4 sec per simulation)
- Caveat: must generate lots of simulations with which to train the GRNN – these simulations scale super linearly with N

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Conclusions

- GRNN was able to accurately replicate the spatio-temporal dynamics of the ABM
  – Rate and final proportion of PHEV adoption (linear and non-linear dynamics)
  – PHEV market penetration with low and high social susceptibility
- Greenness was not as well replicated due to the sole dependency in social susceptibility (less on market conditions)
  – Can be improved with less variable distributions
- GRNN is computationally faster once training datasets exists.

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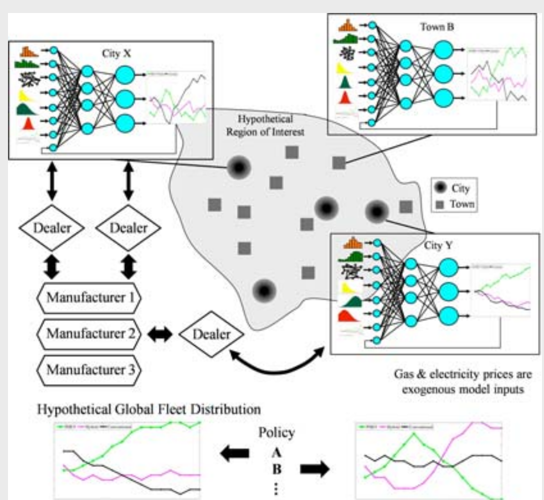
Ongoing Research

- Additional PHEV options
  - Chevy Volt, among others
- Financing options
  - Bring all costs back to present worth
  - Compare monthly expenses to income
- Additional inputs in GRNN
  - How many years out do agents consider during economic analysis (changes with time)

Ongoing and Future Work

- Additional agents
  - Dealerships
  - Manufactures
  - Charging stations owners
- ANNs are used as a surrogate for the city-scale ABM to explore potential policies
  - Federal state and local government agents
  - Tax rebates, energy subsidies, among others



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Questions

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