An Optimization and Agent-Based Socio-Technical Modeling Approach for Engineered Complex Adaptive Systems

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Scope and Hallmarks

Objective

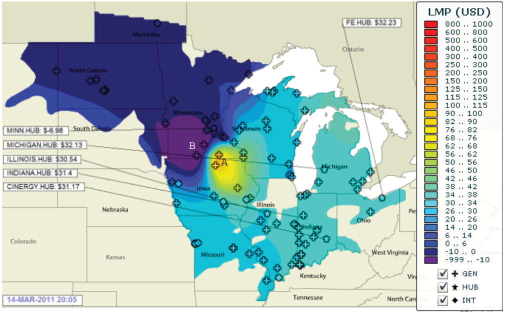
- We examine a class of large-scale engineered systems that are capable of exhibiting complex adaptive system behavior during operation.
- Electric power consumption with dynamic consumer pricing is used to demonstrate the modeling approach.
- Consumers are modeled as interacting agents and identified by preference-behavior classes impacted by innate characteristics, supplier rewards and social relationships.

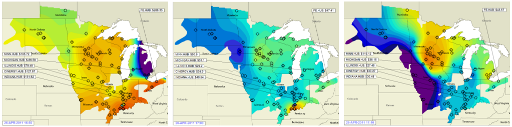
Integration

An Agent-Based Modeling Integrating:

- Social Networks (interpersonal relationships; scale-free & single-scale networks),
- Social Science (friend influence, media impact, and economics),
- Complexity Theory (emergenct behavior and adaptation),
- Diffusion Theory (adaptability and innovativeness), and
- Decision Theory (normative utility and subjective behavior).

Motivation and Application





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(a) 4:50 pm (b) 5:00 pm (c) 5:10 pm

LMP = Locational Marginal Price (System for majority of US)

Supply cost high, a 5% drop in peak demand can save $3B a year.

Motivation and Application

The US electricity power system as an ECAS

- From producer-controlled to consumer-interactive (decreasing centralization),
- Time dependency of the network (Braha and BarYam 2007),
- Scale-free/single-scale feature of the networks (Shargel et al. 2003),
- Decisions based on social relationships and (irrational) preferences,
- Emerging technologies: time-based pricing, smart meters, and home solar systems.

See (Li and Tesfatsion 2009), (ANL 2002), (Barton et al. 2000), and (Wildberger and Amin 1999).

Literature Review and Background

Engineered and mathematically modeled complex network systems

- Dayan-Rosenman (2007) evolutionary structure of networks;
- Barabasi et al. (2002, 2003) statistical mechanics of complex networks, node degree distribution of social networks follows a power law and make scale-free (Exponential Distribution) of single-scale (Gaussian Distribution) networks.
- Hanaki et al. (2007) emergence of cooperative behavior by combining social network dynamics and stochastic learning;
- Amaral et al. (2000) structural properties of SoCal power grid;
- Strogatz (2001) complexity of New York power grid.

Literature Review and Background

Impact of network structure on innovation diffusion

- Montanaria and Saberi (2010) agent adopts behavior from neighbors;
- Guardiola et al. (2002) dynamic pricing in modeling diffusion of innovations;
- Bohlmann et al. (2010) analyze network topologies and communication links between innovator and followers in diffusion;
- Rahmandad and Sterman (2008) compared effect of individual heterogeneity and network topologies on diffusion with agent-based and differential equation models;
- Kempe et al. (2003 and 2005) effect of word-of-mouth recommendations.

Literature Review and Background

Engineered systems involve human designers, controllers, and consumers

- Fowler and Christakis (2008) classify individuals by influence in large social networks (LSNs);
- Tucker (2008) impact of authority structure (managers & workers) can add to or subtract to influences ;
- Leskovec et al. (2006) information cascades in LSNs ;
- Kleinberg (2007) probabilistic & game-theoretic models for information flow and influence.

Literature Review and Background

ABMs used to study the impact of new electricity technologies.

- Hamilton et al. (2009) new technology versus old, and effects of specific externality (fashion effect). Dynamics of technology diffusion among bounded rational agents with uncertainty;
- Zhang and Nuttall (2008) effects of government strategies on promoting new electricity technologies ;
- Athanasiadis et al. (2005) control consumer demands by supporting interaction between consumers;
- Ma and Nakamori (2009) advantages of optimization models and ABM for technological change.

Literature Review and Background

- Agent-based modeling of complex adaptive national electricity markets
  - Comprehensive surveys - Weidlich and Veit (2008), Zhou et al. (2007), and Sensfub et al. (2007);
  - **UK;** Bunn et al. (2001, 2003, 2007, 2009) market power and price-formation of utilities and generators. Bagnall and Smith (2005) multi-agent model for UK power generation market.
  - **Germany;** Bower (2001) studied biding strategies, and an agent-based German electricity market is presented by Sensfub (2007). Wehinger et al. (2010) applied an agent-based model to study the German electricity wholesale market.
  - A**ustralia-NEMSIM;** Grozev et al. (2005), Chand et al. (2008) agent-based model for the CAS interactions between humans, infrastructures and environment of Australia's national electricity market by using the National Electricity Market Simulator (NEMSIM).

Literature Review and Background

- **US;**
  - **AMES:** The Agent-Based Modeling of Electricity Systems (AMES) is designed for computational study of wholesale power market (Tesfatsion (2011), Li and Tesfatsion (2009)).
  - **EMCAS:** Argonne National Laboratory developed the Electricity Market Complex Adaptive System (EMCAS) to analyze the possible impacts on the power system of various events (Conzelmann et al. (2004), North et al. (2002)).
  - **ASPEN-EE:** Sandia National Laboratories presented the Aspen-EE (Electricity Enhancement) to simulate the effects of market decisions in the electric system on critical infrastructures of the US economy (Barton et al. (2000)).
  - **SEPIA:** Honeywell Technology Center (HTC) constructed the Simulator for Electric Power Industry Agents (SEPIA) (Wildberger and Amin (1999)).
  - Pacific Northwest National Laboratory studied power systems as complex adaptive systems (Chassin et al. (2004)).

Literature Review and Background

Table : learning algorithms

Framework	Algorithm
UK	RL
NEMSIM	DT*
Germany	GA & RL
AMES	RL
EMCAS	DT
ASPEN-EE	GA
SEPIA	GA & RL

RL: Reinforcement Learning,
GA: Genetic Algorithm,
DT: Decision Tree,
***** : It is not clear completely

Demand Response

- Demand Response: "Changes in electric usage by end-use customers from their normal consumption patterns in response to changes in the price of electricity over time, or to incentive payments designed to induce lower electricity use at times of high wholesale market prices or when system reliability is jeopardized" DOE (2006).
- US Energy Policy Act of 2005, DOE report quantifies DR benefits.
- US Federal Energy Regulatory Commission (FERC) 2011 order to remove barriers to DR.
- Large-scale social science field experiments by Ayres et al. (2009), academic studies by Allcott (2011) suggest that social and behavioral programs can increase the efficiency of load management programs.

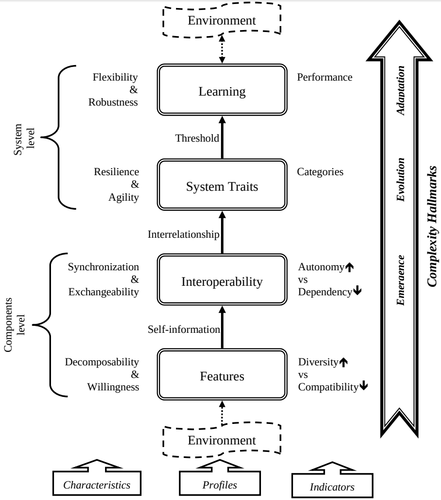
Controlling/Engineering Engineered Complex Adaptive Systems

- CAS Hallmarks
  - *Emergence* capability of components of a system to do something or to present a new behavior in interaction and dependent to other components that they are unable to do or present individually.
  - *Evolution* process of change and agility for the whole system.
  - *Adaptation* ability of systems to learn and adjust to a new environment to promote their survival.
- ECASs
  - Objectives are artificially defined and interoperabilities between components can be manipulated to achieve desired goals,
  - Objectives and interoperabilities of natural systems are naturally embedded.
  - Does not preclude unintended complexity behaviors but allows for a design and control aspect of the system.

A Framework for ECASs

❇ **Features**:
components readjust themselves continuously;
❇ **Interoperabilities**:
components update their interdependences;
❇ **System Traits**:
system tries to improve its efficiency and effectiveness;
❇ **Learning**:
system has flexibility to perform in unforeseen situations;

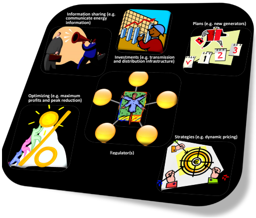
✿ **Assumptions:**
$C_i^q(w)$: consumption of electricity at time w for pattern i in period q.
Where,
$(i = 1, \ldots, n)$, $0 \leq w \leq w_0$, and $(q = 1, \ldots, T)$.
X_i^q: population of pattern i at period q.
P_i^q: percentage of consumers with pattern i at period q.
b_i: growth rate of pattern i.
E^q: entropy of the system at period q.
D_i^q: individual dis-uniformity of pattern i at period q.
D^q: total dis-uniformity of the system at period q.



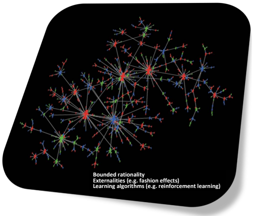
Definitions

- *Individual Dis-uniformity*, Eq. 2, is the sum of squared error of differences between the current state of a component and its goal state (here is the average daily consumption of the consumer agent).
- *Total Dis-uniformity*, Eq. 3, is the mean squared error of differences between the current state of components and the goal state of the whole system (total average consumption).
- *Interoperability* is the capability of two or more components to provide information and to use exchanged information to operate together in a predictable way and without significant user intervention. Intuitively, it measures the effects of a component in the operations of the other one.
- *Conditional interoperability* is the expected value of the effect of two components on each other given the third component is added to the system as a catalyst (we do not need to study the state of a catalyst but it can increase or decrease the interoperability between other components).
- *Entropy* measures the disorder in a population of consumers with n patterns of behaviors. We defined the *joint probability* to find simultaneously two patterns in their possible states.

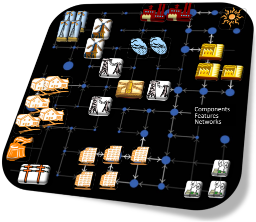
Proposed Three Layer Model Structure



(d) Decision Layer



(e) Social Layer



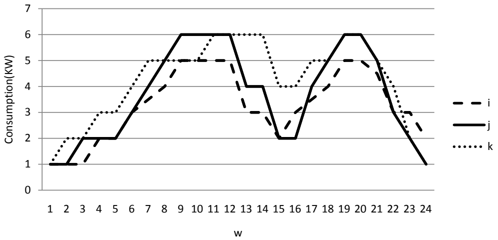
(f) Physical Layer

- Strategies (e.g. dynamic pricing),
- Optimizing (e.g. maximum profits and peak reduction),
- Plans (e.g. new generators),
- Investments (e.g. transmission and distribution infrastructure),
- Information sharing (e.g. communicate energy information).

- Interrelationships between agents and preferences,
- Bounded rationality for agents and externalities (e.g. fashion effects),
- Some non-physical attributes of agents (e.g. attractiveness),
- Learning algorithms (e.g. reinforcement learning) and adaptation scenarios.

- Features, mechanism of components of the system, and their network.
- Generators (e.g. main power plant, wind forms, solar panels, and small generators),
- Transmission, and distributors,
- Consumers (e.g. homes, businesses, and industries).

Patterns of behaviors



- $C_i^q(w)$: consumption of electricity at time w for pattern i period q. Where, $(i = 1, ..., n)$, $0 \leq w \leq w_0$, and $(q = 1, ..., T)$. X_i^q: population of pattern i at period q.
- Average daily consumption of a pattern i at period q: $\overline{C_i^q} = \frac{\int_0^{w_0} C_i^q(w)\,dw}{w_0}$.
- Average daily consumption per consumer (we remove q's here to increase its readability): $\overline{C} = \int_0^{w_0} \left(\frac{\sum_{i=1}^{n} C_i(w) X_i}{w_0 \sum_{i=1}^{n} X_i}\right) d_w$.

Entropy and Dis-uniformity

- Without Influence, population of pattern i $(X_i; i = 1, ..., n)$, $\Delta X_i = b_i X_i$. Entropy, $E = -\sum P_i \log_2 P_i$, of the system.

$$\frac{\Delta E}{\Delta q} = \sum b_i P_i (\sum P_i \log_2 P_i - \log_2 P_i). \quad (1)$$

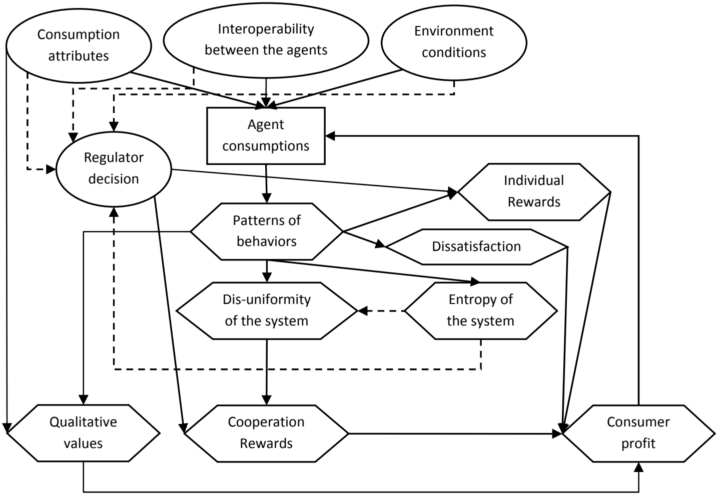
- Individual Dis-uniformity:

$$D_i^q = \int_0^{w_0} (C_i^q(w) - \overline{C_i^q})^2 dw, \quad i = 1, ..., n, \quad q = 1, ..., T. \quad (2)$$

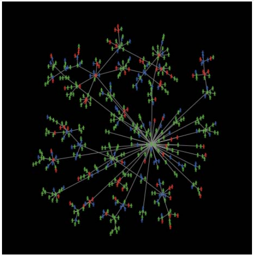
- Aggregate Dis-uniformity: consumers cooperate to have uniform aggregate consumption at each period,

$$D^q = \int_0^{w_0} (\frac{\sum_{i=1}^n (C_i^q(w) - \overline{C_i^q}) X_i^q}{\sum_{i=1}^n X_i^q})^2 dw. \quad (3)$$

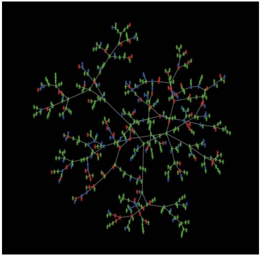
Decision Makers/Agents



Complex network



(g) Scale-free, $\lambda \approx 2$



(h) Single-scale (Gaussian)

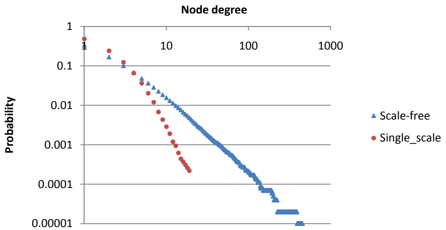


Figure : Log-log plot

CLASS OF INTEROPERABILITIES

- Interoperability class defined by node degree; Class defines how agents influence each other. Given a set of α, β

$$Lin(\alpha_{\delta_\upsilon}, \beta_{\delta_\upsilon}) = \alpha_{\delta_\upsilon}.ln(|E(G)|) - \beta_{\delta_\upsilon}, \tag{4}$$

where,

$$\begin{aligned} \delta_\upsilon \in \{INF, EF, LF, ISO\}, &\text{class of agent}\upsilon \\ \alpha_{INF} > \alpha_{EF} > \alpha_{LF} > \alpha_{ISO}, \\ \beta_{INF} > \beta_{EF} > \beta_{LF} > \beta_{ISO}, \end{aligned} \tag{5}$$

$|E(G)|$ shows the number of links in the social network G.
Deg_υ is the degree of Node υ in the network.

$$\delta_\upsilon = \begin{cases} INF, & \text{if} \quad Deg_\upsilon \geq Lin(\alpha_{INF}, \beta_{INF}), \\ EF, & \text{if} \quad Lin(\alpha_{EF}, \beta_{EF}) \leq Deg_\upsilon < Lin(\alpha_{INF}, \beta_{INF}), \\ LF, & \text{if} \quad Lin(\alpha_{LF}, \beta_{LF}) \leq Deg_\upsilon < Lin(\alpha_{EF}, \beta_{EF}), \\ ISO, & o.w. \end{cases} \tag{6}$$

Interoperabilities

Interoperability Matrix $I^c_{\delta_\upsilon \delta_z}$

- Let $I^c_{\delta_\upsilon \delta_z}$ represent *interoperability between classes of agents*.
- $I^c_{\delta_\upsilon \delta_z}$ is a monotonic function of the influence that a agent of Class δ_z has on a agent of Class δ_υ.
- Interoperability is a positive number with maximum of one where, $I^c_{\delta_\upsilon \delta_z} = 0$ shows autonomic (independent) class of agents and $I^c_{\delta_\upsilon \delta_z} = 1$ when they follow each other (identical).

Table : Interoperability between consumer agents

$I^c_{\delta_\upsilon \delta_z}$	INF	EF	LF	ISO
INF	0.8	0.6	0.4	0.3
EF	0.6	0.5	0.3	0.2
LF	0.4	0.3	0.2	0.1
ISO	0.3	0.2	0.1	0.001

Interrelationships

- Interrelationship Between Agent Pairs, $\Re$
  - *Self-preference*, $0.5 \leq \theta_{\upsilon z} \leq 1$, lets agents vary their individual interoperability. Note could have $\theta_{\upsilon z} = \Theta_{\upsilon}.\Theta_{z}$
  - To simplify the formulation we use *average self-preference*, $\theta_{\upsilon \delta_z} = \frac{\sum_{z \in \delta_z} \theta_{\upsilon z}}{X_{z \in \delta_z}}$ (Agent υ with class δ_z).

$$\Re_{\upsilon i} = \frac{\sum_{\delta_z} \theta_{\upsilon \delta_z}.I^{c}_{\delta_\upsilon \delta_z}.X_{\delta_{zi}}}{\sum_{\delta_z} \sum_{i} X_{\delta_{zi}}}, \quad i = 1, ..., n, \upsilon = 1, ..., Q, \tag{7}$$

Note i = pattern; $X_{\delta_{zi}}$ = no. agents in class δ_z with i

- Select an appropriate pattern as a switching target:

$$switch^{q}_{\upsilon} = arg_i\{\max(\Re_{\upsilon i})\}, \quad \forall i, \Re_{\upsilon i} > \Upsilon_{\upsilon}. \tag{8}$$

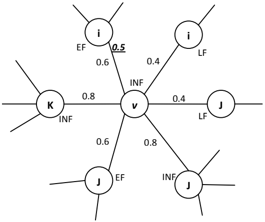
$$switch^{q}_{\upsilon} = arg_i\{\max(\Re_{\upsilon i})\}, \quad \forall i \neq \text{Pattern}(\upsilon), \Re_{\upsilon i} > \Upsilon_{\upsilon}. \tag{9}$$

Example

Interoperability between agents are assigned to the arcs.

If agent υ, does not have any self-preference (i.e. $\theta_{\upsilon z} = 1$):

- $\Re_{\upsilon i} = \frac{0.6+0.4}{6} = 0.17$,
- $\Re_{\upsilon j} = \frac{0.6+0.4+0.8}{6} = 0.3$,
- $\Re_{\upsilon k} = \frac{0.8}{6} = 0.13$.
- From Eq. 8, $switch = j$ in all cases.
- From Eq. 9, $switch = i$ if Pattern(υ)$= j$ and $switch = j$ if Pattern(υ)$\neq j$.



If decision maker υ "prefers" to have half of its maximum interoperability with the EF class of pattern i ($\theta_{\upsilon i} = 0.5$):

- $\Re_{\upsilon i} = \frac{0.5*0.6+0.4}{6} = 0.12$,
- $switch = k$ if we use Eq. 9 and Pattern(υ)$= j$.

Attributes of Agents

Each agent runs a pattern that has three attributes (price, attentiveness, and attractiveness)

- Price defines the total cost of consumption in a 24 hour cycle time for the related pattern.
- Attentiveness shows how fast and easy consumers can make a decision to switch to this pattern.
- Attractiveness shows the effects of advertisement or other fashion attributes of the patterns.

The *Utility Value* U_υ, is the weighted average of the *desirability scores* $\Omega_{\upsilon s}$ of its pattern attributes . Agents can assign their own importance weight $W_{\upsilon s}$, to attribute S.

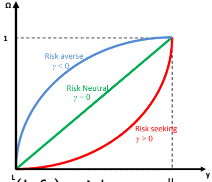
$$U_\upsilon = \frac{\sum_s W_{\upsilon s}\Omega_{\upsilon s}}{\sum_s W_{\upsilon s}}, \quad \upsilon = 1, ..., Q, s = 1, 2, 3. \tag{10}$$

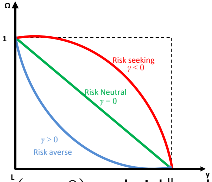
Desirability and value

An agent's total utility U_υ (value) of a pattern is a weighted average of desirability scores $\Omega_{\upsilon s}$:

$$\Omega_{\upsilon s} = \begin{cases} \frac{1-exp(\gamma_{\upsilon s} * \frac{y_s - L_s}{U_s - L_s})}{1-exp(\gamma_{\upsilon s})}, & \text{if} \quad \gamma_{\upsilon s} \neq 0, \quad \upsilon = 1, ..., Q, s = 1,2,3, \\ \frac{y_s - L_s}{U_s - L_s}, & \text{if} \quad \gamma_{\upsilon s} = 0, \quad \upsilon = 1, ..., Q, s = 1,2,3. \end{cases} \tag{11}$$

$$\Omega_{\upsilon s} = \begin{cases} \frac{1-exp(\gamma_{\upsilon s} * \frac{U_s - y_s}{U_s - L_s})}{1-exp(\gamma_{\upsilon s})}, & \text{if} \quad \gamma_{\upsilon s} \neq 0, \quad \upsilon = 1, ..., Q, s = 1,2,3, \\ \frac{U_s - y_s}{U_s - L_s}, & \text{if} \quad \gamma_{\upsilon s} = 0, \quad \upsilon = 1, ..., Q, s = 1,2,3. \end{cases} \tag{12}$$





targeting maximum (left): risk-averse agents $(\gamma < 0)$ and risk-seeking agents $(\gamma > 0)$,
targeting minimum (right): risk-averse agents $(\gamma > 0)$ and risk-seeking agents $(\gamma < 0)$.

Decision Rules

Agent's Optimal Choice

$$\max \pi_{\upsilon}^{q} = k_{\hat{r}} \hat{R}^{q} + k_{r} R_{\upsilon}^{q} + k_{u} U_{\upsilon}^{q} - k_{\varphi} \varphi^{q}, \tag{13}$$

where,

$$\hat{R}^{q} = f_0(D^{q}), \text{cooperation reward}, \quad \forall q, \tag{14}$$

$$D^{q} = g_0(C_i^{q}(w)), \text{total dis-uniformity}, \quad \forall i, q, w, \tag{15}$$

$$R_{\upsilon}^{q} = f_0'(D_{\upsilon}^{q}), \text{individual reward}, \quad \forall \upsilon, q, \tag{16}$$

$$D_{\upsilon}^{q} = g_0'(C_i^{q}(w)), \text{individual dis-uniformity}, \quad \forall \upsilon, i, q, w, \tag{17}$$

$$U_{\upsilon}^{q} = f_1(\Omega_{\upsilon s}), \text{quantitative values}, \quad \forall \upsilon, q, s, \tag{18}$$

$$\varphi_{\upsilon}^{q} = f_2(C_{\upsilon}^{q}(w), C_{\upsilon}^{q-1}(w)), \text{dissatisfaction}, \quad \forall \upsilon, q, w. \tag{19}$$

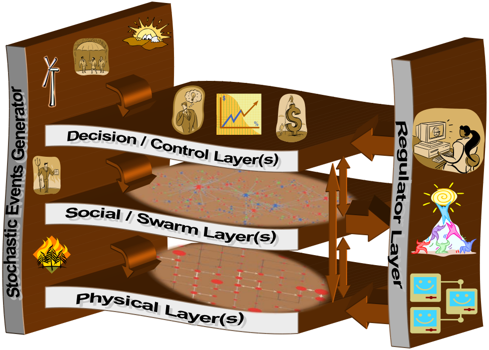
IRRATIONALITY

- **Irr-I:** The probability that agent υ does not switch to the new pattern even if the objective function of the new pattern is higher than the objective function of the old pattern.
- **Irr-II:** The probability that agent υ switches to a new pattern even if the objective functions do not satisfy the switching threshold.

$$Prob_\upsilon = \frac{exp(k_I * Obj_{New})}{exp(k_I * Obj_{New}) + exp(k_I * Obj_{Old})} \tag{20}$$

where, k_I shows the sensitivity of the agents to differences between the objective functions (the higher the k_I, the more sensitive agents).

Integration and Possible Outcomes



- When (what day) is the best time to trigger a demand response event?
- How much trigger is required?
- What type of events/trigger are more effective and efficient?
- Who are the event recipient? What is the schedule to receive their triggers?

Variables

Table : State variables for running the simulation

300 runs of 400 periods each

Parameter	Variable	Range	Units	Default	Area*
Initial Population	$\upsilon = 1, \ldots, \sum_i X_i$	100- $\inf$	# of consumers	500	E
Initial Patterns	$\frac{X_i}{\sum_i X_i}, i = 1, 2, 3$	0 to 1	% of total population	0.15,0.65,0.20	E
Growth Rate	b_i, i=1,2,3	0 to 1	% of pattern population	0, 0, 0	E
Max Link Generation	ϱmax	1 to 10	number	1	E
Price	S_1	3-8	Currency $(cents/KWh)$	5, 5, 5	C
Attentiveness	S_2	2-5	Time $(min/decision)$	4, 4, 4	C
Attractiveness	S_3	1-10	Qualitative	3, 3, 3	C
Desirability Coefficient	$\gamma_{\upsilon s}$	∼Normal $(0, 4)$	N/A	N/A	A
Attribute Weight	W_υ	∼Normal $(1, 0.2)$	N/A	N/A	A
Average Self-preference	$\theta_{\upsilon \delta_z}$	∼Uniform $(0.5, 1)$	N/A	N/A	A

* Here E, C, and A stand for Environment, Consumption and Agents respectively.

Analyzing Behaviors

The entropy of the system is less than 0.3364 i.e. when at least 95% of agents converge to a pattern.

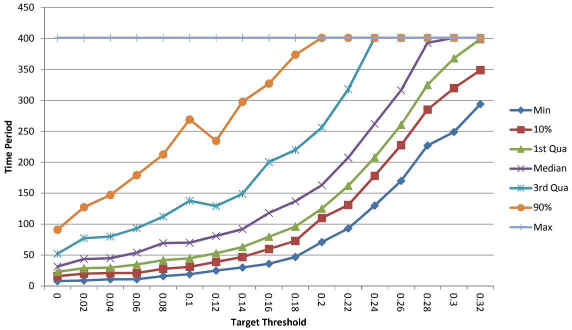
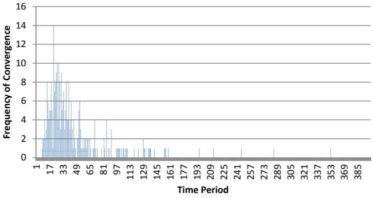
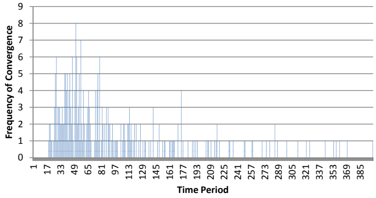


Figure : Convergence of the Entropy

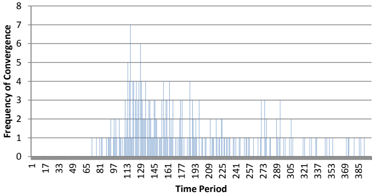
Analyzing Behaviors



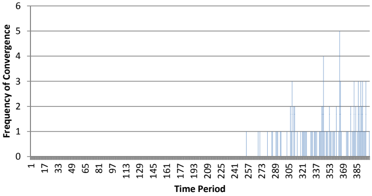
(a) Target-Threshold=0



(b) Target-Threshold=0.1



(c) Target-Threshold=0.2



(d) Target-Threshold=0.3

Figure : Distribution of convergence to Pattern i

Analyzing Behaviors

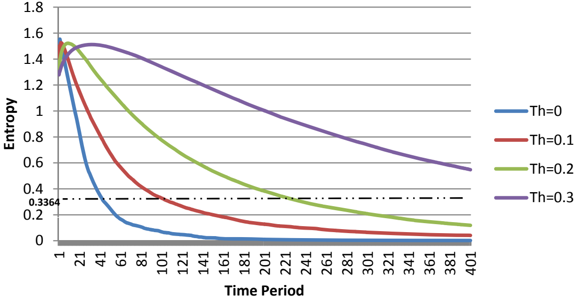


Figure : Convergence of the Average Entropies

Analyzing Behaviors

$$\sum_i \sum_q |P_{iq}^{(1)} - P_{iq}^{(2)}| \quad i = 1, 2, 3; \quad q = 1, ..., 400. \tag{21}$$

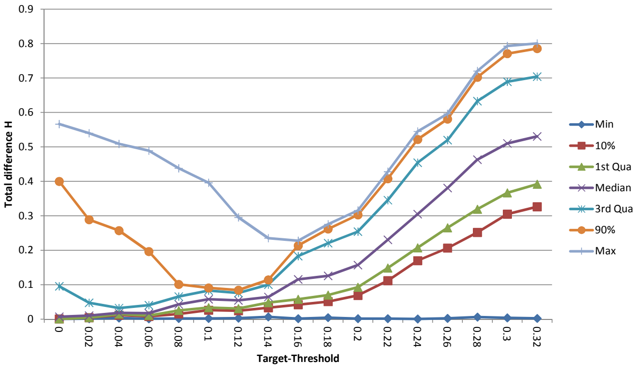
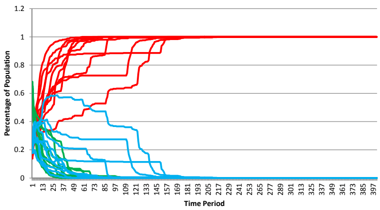
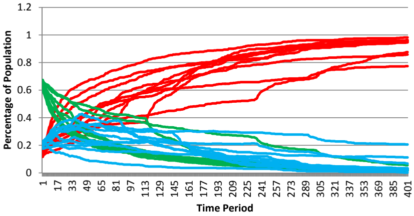


Figure : Total difference with and without (5% participate in DR) a social network

Analyzing Behaviors

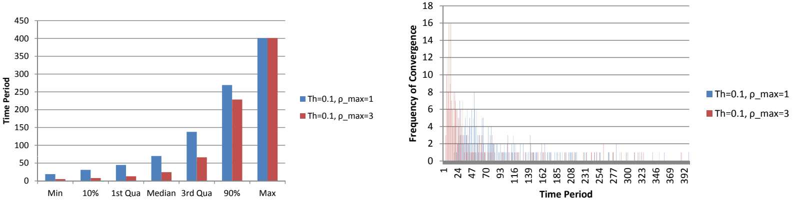


(a) Target-Threshold=0.1



(b) Target-Threshold=0.3

Improving Effect of the Social Network



(a) Convergence of the Entropy

(b) Distribution of convergence to Pattern i

Figure : Comparison of Max Links $\varrho_{max} = 1$ and $\varrho_{max} = 3$

Externalities and irrationality

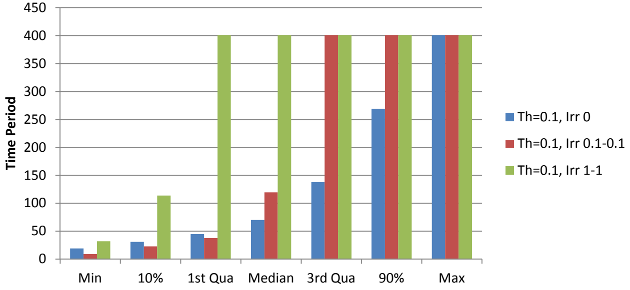
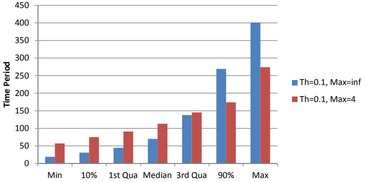
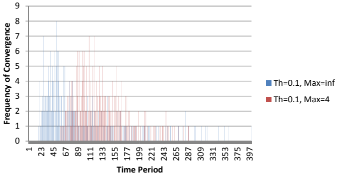


Figure : Effects of Irrationality

Effects of saturated interrelationships



(a) Convergence of the Entropy



(b) Distribution of convergence to Pattern i

Figure : Effect of saturated friendship on the topology of the network

From scale-free, Power law (BLUE) to single-scale, Gaussian (RED) topology

Sensitivity to the Price of Pattern i

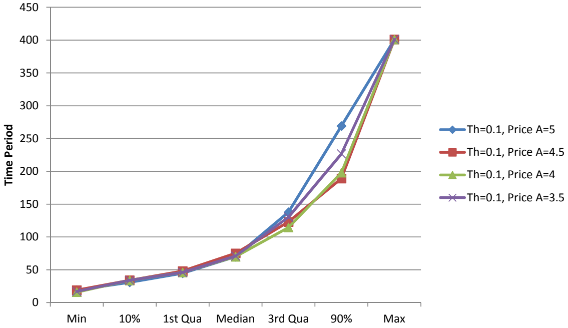


Figure : Sensitivity to the Price

SUMMARY

- Embedded an optimization model in an agent-based simulation to study human behaviors in a complex adaptive system.
- Analyze the structure of a human decision network and show how agents behave as a result of their interoperability through a scale-free network and in relationship with the environment.
- Control and predict the behavior of dis-uniformity and entropy in a power system. Decrease the dis-uniformity while considering the stable and equilibrium states.
- Agents dynamically update their optimization models at each time increment on the basis of new information and observed system behavior and may emerge to new patterns.
- This optimized emergence causes optimized evolution in the system.

For more details and references see:

M. Haghnevis and R. Askin, “A modeling framework for engineered complex adaptive systems,”IEEE Systems Journal, vol. 6, no. 3, pp. 520-530, 2012. Special Issue; Complexity in Engineering: from Complex Systems Science to Complex Systems Technology.

M. Haghnevis and R. G. Askin, “Modeling properties and behavior of the US power system as an engineered complex adaptive system,”in proceedings of the 2011 CAS AAAI Fall Symposium, (Arlington, VA, USA), Association for the Advancement of Artificial Intelligence, November 2011.

M. Haghnevis, A. Shinde, and R. G. Askin, “An integrated optimization and agent-based framework for the U.S. power system,”in proceedings of the Complex Adaptive Systems 2011, (Chicago, IL, USA), Missouri University of Science and Technology, October-November 2011

Appendix

Complex Adaptive Systems

- Complex Systems
  - System structure:
    - displays no or incomplete central organizing for the system organization (prescriptive hierarchically controlled systems are assumed to not be complex systems),
    - behavioral interactions among components at lower levels are revealed by observing behavior of the system at higher level.
  - Analysis of system behavior:
    - analyzing components fails to explain higher level behavior,
    - reductionist approach does not satisfactorily describe the whole system.

- Complex Adaptive Systems (CASs) consist a huge number of interacting components. Self-organization, emergent phenomenon, evolutionary behaviors, and adaptation are basic hallmarks of such systems.

Agent-based Modeling and simulation

- Agent-based modeling and simulation (ABMS) aims to model interacting autonomous agents
  - This topic promised to propose novel approaches when it was presented in 1990s; however,
  - Initial discussion about this subject began in 1970s based on Cellular Automata (CA).
- Agent-based models include agents, their relationships, and their environment.
  - Agents have behaviors and interactions with other agents and the environment. Their behaviors (often described by simple rules) relate information sensed by the agents to their decisions.
  - Interactions include a topology of connectedness and protocols for the interactions.
  - Agents may be affected by their positions in the environment.

see (Macal and North 2010 and 2006) (Siebers wt al. 2010), (Suematsu et al. 2003), and (Anderson 1999)

The characteristics of ABMs

- Agents:
  - Agents act autonomously (self-directed) i.e., they make independent decision without external direction, however, they interact with their environment and other agents (their interactions influence their behaviors).
  - An agent is self-contained (uniquely identifiable) i.e., we can determine what is part of an agent or not.
  - An agent has a state that represents the attributes of its current situation.
- Interactions:
  - The topology of interactions defines who is, or could be, connected to who.
  - The protocols of interactions are the mechanisms of the dynamics of the interactions.
  - These specifications limit the agents to their local information.
- Agent-based systems are decentralized i.e. there is no global control or authority, however, some agents may have more power to influence other agents.

ABMs and CASs

- These characteristics enable agents to be:
  - adaptive (can learn based on experiences),
  - goal-directed (adjust themselves or their interactions based on a goal), and
  - heterogeneous (their attributes and behaviors may vary and change dynamically).
- The most important advantage of ABMs is their capability to explicitly model complex adaptive systems (CASs).
  - Complex behaviors such as altruistic versus selfish and cooperation versus competition can be studied by agent-based models.
  - ABMs can study and analyze the complexities that arise from individual actions and interactions that exist in the real world by bottom-up iterative design methodologies.

ABMs, CASs, and OOP

- ABM and CAS
  - Instead of reducing nonlinear systems to a set of causal variables and error terms, ABMs show how complex adaptive outcomes flow from simple phenomena and depend on the way that agents are interconnected.
  - Rather than aggregating outcomes to find a total equilibrium, ABMs present the evolution of outcomes as the result of the efforts of agents to achieve better fitness
- ABM and OOP
  - Agent-based simulation and object-oriented simulation are not the same, however, object-oriented modeling is a useful basis for ABMs.
  - An agent can be considered as a self-directed (autonomous) object that has the capability to make decisions individually based on its situation and its interactions with other agents.

Tools

Different tools are developed for modeling and simulating SD (e.g. Vensim™, ModelMaker™), DE (e.g. Arena™, SLAM™, AutoMod™), and ABM (e.g. NetLogo™, Repast™)

Table : Characteristics of different types of modeling paradigms

	DE	SD	ABM
Basic elements	entities, resources, blocks	entities, flow	agents, interactions, environment
Modeling approach	top-down	bottom-up	bottom-up
Control	centralized	centralized	decentralized
Components	passive	active	active
Data	objective	objective	subjective
Strategy	no	no	yes
Population	homogeneous	homogeneous	heterogeneous

- We can not consider ABMS as a replacement of all other traditional techniques.
    - Typically, ABMs need more detailed information and computation times.
    - Even with powerful computers, modelers face trade-offs between complex detailed individual behaviors and simple decomposable models.
    - Also, frameworks for verification and validation of ABMS are still incomplete and fragmented.
- Generally, we may propose ABMs in the following situations:
    - When our goal is to model evolving outcomes of individual behaviors,
    - When the components operate in interaction with each other and their environment based on a topology and a protocol,
    - When self-organizing agents can learn and adopt to new situations and make evolution in a system,
    - When heterogeneous agents can make strategic decisions to cooperate or collude or compete to achieve their goals.

Dominance Types

- *Dominance*: behavior i dominates behavior j ($i \gtrapprox j$) if $D_i \leq D_j$.
- *Strict Positive Dominance*: behavior i strictly positively dominates behavior j ($i \succ j$) if $D_i < D_j$, $|C_i(w) - \overline{C}| \leq |C_j(w) - \overline{C}|$ for all w and $sgn(C_i(w) - \overline{C}) = sgn(C_j(w) - \overline{C})$ for all w.
- *Positive Dominance*: behavior i positively dominates behavior j ($i \succcurlyeq j$) if $D_i < D_j$, $|C_i(w) - \overline{C}| > |C_j(w) - \overline{C}|$ for some w and $sgn(C_i(w) - \overline{C}) = sgn(C_j(w) - \overline{C})$ for all w.
- *Strict Negative Dominance*: behavior i strictly negatively dominates behavior j ($i \succsim j$) if $D_i < D_j$, $|C_i(w) - \overline{C}| \leq |C_j(w) - \overline{C}|$ for all w and $sgn(C_i(w) - \overline{C}) \neq sgn(C_j(w) - \overline{C})$ for all w.
- *Negative Dominance*: behavior i negatively dominates behavior j ($i \curlyeqsucc j$) if $D_i < D_j$, $|C_i(w) - \overline{C}| > |C_j(w) - \overline{C}|$ for some w and $sgn(C_i(w) - \overline{C}) \neq sgn(C_j(w) - \overline{C})$ for all w.

Summary of Emergence

	$-\log_2 P_i > E$		$-\log_2 P_i < E$	
	$b_i > b_j$	$b_i < b_j$	$b_i > b_j$	$b_i < b_j$
$i \succ j$	$E \uparrow \wedge D \downarrow$	$E \downarrow \wedge D \uparrow$	$E \downarrow \wedge D \downarrow$	$E \uparrow \wedge D \uparrow$
$i \succcurlyeq j$	$E \uparrow \wedge D \downarrow$	$E \downarrow \wedge D \uparrow$	$E \downarrow \wedge D \downarrow$	$E \uparrow \wedge D \uparrow$
$i \succsim j$	$E \uparrow \wedge D \downarrow$ (1), $D \uparrow$ (2)	$E \downarrow \wedge D \uparrow$	$E \downarrow \wedge D \downarrow$ (1), $D \uparrow$ (2)	$E \uparrow \wedge D \uparrow$
$i \succapprox j$	$E \uparrow \wedge D \downarrow$ (1), $D \uparrow$ (2)	$E \downarrow \wedge D \uparrow$	$E \downarrow \wedge D \downarrow$ (1), $D \uparrow$ (2)	$E \uparrow \wedge D \uparrow$

(1) if $\sum X_i \int (C_i(w) - \overline{C_i})dw > \sum X_j \int (C_j(w) - \overline{C_j})dw$,
(2) if $\sum X_i \int (C_i(w) - \overline{C_i})dw < \sum X_j \int (C_j(w) - \overline{C_j})dw$.

Theorem V (mechanisms of components): If $i \succapprox j$, i.e., i's dominate j's, dis-uniformity of the system is decreasing in period if the entropy increases in period when $-\log_2 P_i > E$ or if the entropy decreases in period when $-\log_2 P_i < E$ while, $\sum X_i \int (C_i(w) - \overline{C_i})dw < \sum X_j \int (C_j(w) - \overline{C_j})dw$ for both conditions.

Applying this integrated optimization and agent-based model has the following benefits for the US power system and leading to a reduction in investment on the power grid infrastructure:

- motivates consumers to balance the total workload by providing incentives and social education,
- encourages agents to cooperate with the grid regulators in high stress times and environments by communicating energy information,
- increases the grid's security and reliability by analyzing its behavior during accidents or system faults,
- allows studying complex system response to dynamic pricing and other control strategies,
- predicts and controls emergent behavior of the agents and system evolution by mathematical modeling in respect to economic incentives and social interactions.