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Modeling Properties and Behavior of the US Power System as an Engineered Complex Adaptive System
Extended Abstract

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Introduction

Classically, system analysts consider the physical world as an collection of components and their approximately linear interactions. This assumption allows studying a system by reductionism (bottom-up understanding of decomposed components and then aggregating the partitions) to analyze the whole system behaviors. Today, holism evidences that the sum of components fails to describe systems comprised of myriad interoperabilities between agents. Emergent, evolutionary, and adaptive behaviors of the real-world depict a fruitful source of inspiration for modeling behavior of complex adaptive systems (CAS). Traditional mathematical and engineering modeling of CASs (such as equilibrium or game theory models) are still incomplete and fragmented. They are usually unable to study real characteristics of agents and their decision behaviors. Complexity theory and concepts are well studied in the literature (Couture 2007) and (Couture 2006b). Also, researchers tried to present mathematical methods and measures to study CASs (Couture 2006a), (Bar-Yam 2004b), (Bar-Yam 2004a), and (Bar-Yam 2000).

This research aims to define a novel framework and platform to employ engineering and mathematical models to study adaptive dynamics in certain engineered complex adaptive systems (ECAS). We analyze a class of decentralized heterarchial complex systems to infer emergent behavior of the components, evolution processes, and adaptations of the whole systems. While the US electric power system will be utilized for demonstration and validation, the framework has applicability to the general class of ECASs. Conditioned on parameterization of the framework, a theorem will be presented to calibrate current situation and predict future behaviors of an ECAS.

The huge growth of the US power system (3.7 billion KWh consumption in 2009 i.e. 13 times greater than 1950 and expected growth to 4.88 billion KWh by 2035 (EIA), consumer-interactive controls, time dependency of the market, and complexity in its network topology are main reasons to consider the US power system as an ECAS. Locational Marginal Price (LMP) of electricity vary by time, location, and consumer type (e.g. Fig 1 provides the LMP contour map of the Midwest ISO (MISO) in April 26,2011 at 17:25 that may change totally in the next 5 minutes). This adaptive complexity in consumer behavioral level motivates us to study the interrelationships between consumers, their interoperability, and willingness to cooperate or compete in the system. Some previous studies considered other parts of the US power market, e.g. physical level or business issues, as an ECAS (Li and Tesfatsion 2009), (Conzelmann et al. 2004), (ANL), (Barton et al. 2000), and (Wildberger and Amin 1999).

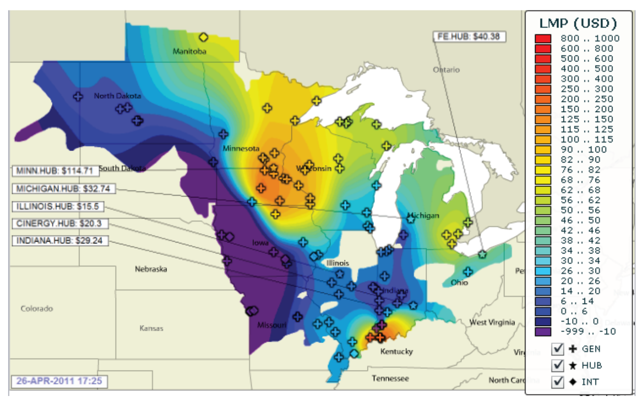

Figure 1: LMP contour map of the Midwest ISO

Applying this integrated model has the following benefits for the US power system:

- Reduction of dis-uniformity in electricity consumption to reduce investment in new generators, transmission and distribution infrastructure.
- Communicates energy information to encourage people to change their behavior in high stress times or vulnerabilities (e.g., specific weather, high demand days, and accident or fault in power lines or generators).
- Allows analyzing changes in the behaviors by increasing the effectiveness of the dynamic pricing strategies.

Engineered CASs Framework

A multi-profile descriptive framework is developed to calibrate the current structure of an ECAS and to predict its dynamic behaviors. Four-tuple profiles of ECASs, their characteristics, and the proper measures are presented in Table 1.

Components have both individual features and interoperabilities. Systems have traits such as resilience that contribute to adaptability and the potential to learn.

Table 1: Profiles of the framework for ECASs

Profile	Characteristics	Indicators
Features	Decomposability, Willingness	Diversity vs. Compatibility
Interoperabilities	Synchronization, exchangeability	Autonomy vs. Dependency
System Traits	Resilience, Agility	Categories
Learning	Flexibility, Robustness	Performance

At an aggregate level, we describe the system complexity with dissection of features (Entropy, E), interoperabilities (sensitivity and interrelationship to neighbors, R), system traits, and learning (milestones for changes in the system performance i.e. Evolution Thresholds, τ). In addition a system may have a goal. In our case, it is to minimize dis-uniformity of electricity consumption. Entities (consumers) in the system are classified into behavioral types defined by patterns of daily consumption.

Notation:

$i = 1, ..., n$: set of patterns of behaviors,

$X_i(t)$: population of pattern i at period t,

$P_i(t)$: proportion of entities with pattern i at period t,

b_i: fitness rate of pattern i (static in different periods),

$C_i^t(w)$: electricity consumption of pattern i at time w for period t.

Short term cyclic time w may correspond to the hours of a day while t refers to months or seasons. We remove t's in the following formulas except when necessary to compare different periods to increase readability.

Features Dissection

Assume the population X_i grows exponentially by Eq. 1 where, $\frac{\Delta X_i}{\Delta t} = b_i X_i$.

$$X_i(t+1) = b_i.X_i(t) + X_i(t), \quad i = 1, ..., n. \tag{1}$$

Then the growth of entropy, $E = -\sum P_i \log_2 P_i$, follows Eq. 2 where, $P_i = \frac{X_i}{\sum X_i}$.

$$\frac{\Delta E}{\Delta t} = \sum b_i P_i (\sum P_i \log_2 P_i - \log_2 P_i), \quad i = 1, ..., n. \tag{2}$$

The dis-uniformity variation of pattern i by time is shown in Eq. 3 where, $\overline{C_i^t} = \frac{\int_0^w C_i^t(w)dw}{w}$.

$$D_i(t) = \int_0^w (C_i^t(w) - \overline{C_i^t})^2 dw, \quad i = 1, ..., n, \quad w \ll t \tag{3}$$

One part of the decision objective is to minimize the total dis-uniformity, Eq. 4 (consumers cooperate to have less fluctuations in the total consumption in different times for peak reduction or load balancing).

$$D = \int_0^w (\frac{(\sum_i C_i(w) X_i) - \frac{\int_0^w \sum_i C_i(w) X_i dw}{w}}{\sum_i X_i})^2 dw, \tag{4}$$

We define behavior i *dominates* behavior j ($i \succapprox j$) if $D_i \leq D_j$. Table 2 defines other possible types of dominance in the patterns of behaviors conditioning on values and signature of variation in short-term pattern of behaviors, $\sigma(w)$ where, $\sigma(w) = C(w) - \overline{C}$. For example i exhibits Strict Positive Dominance over j if $|\sigma_i(w)| \leq |\sigma_j(w)|$ and $sgn(\sigma_i(w)) = sgn(\sigma_j(w))$ for all w. To control decomposability and willingness of components of a CAS in all dominance cases we can apply the theorem of *mechanisms of component*, defined as follows.

Table 2: Definition of dominance possibilities

Dominance	symbol	$\lvert\sigma_i(w)\rvert$	$sgn(\sigma_i(w)), \forall w$
Strict Positive	$i \succ j$	$\leq \lvert\sigma_j(w)\rvert \forall w$	$= sgn(\sigma_j(w))$
Positive	$i \succcurlyeq j$	$> \lvert\sigma_j(w)\rvert \exists w$	$= sgn(\sigma_j(w))$
Strict Negative	$i \succsim j$	$\leq \lvert\sigma_j(w)\rvert \forall w$	$\neq sgn(\sigma_j(w))$
Negative	$i \curlyeqsucc j$	$> \lvert\sigma_j(w)\rvert \exists w$	$\neq sgn(\sigma_j(w))$

where, $\sigma_i(w) = C_i(w) - \overline{C_i}$

Theorem (mechanisms of components): Consider the case where $i \succapprox j$ and $\sum X_i \int \sigma_i(w)dw < \sum X_j \int \sigma_j(w)dw$. Dis-uniformity of the system is then decreasing in time if the Entropy increases in time when $-\log_2 P_i > E$ or if the Entropy decreases in time when $-\log_2 P_i < E$.

This theorem is a result of analyzing detailed dominance that is summarized in Table 3 (see (Haghnevis and Askin 2010) for proofs). It shows how E and D are decreasing ($\downarrow$) or increasing ($\uparrow$) in time for all dominance cases ($i : j$) conditioning on fitness rates ($b_i : b_j$) and the entropy situations ($\log_2 P_i : E$). For example assume n different patterns of behavior ($i = 1, ..., n$) in population S, $b_k \geq 0$, $\forall k \in S$ and $i \succ j$, for $i \in S'$ and $j \in S - S'$. Then $E < -\log_2 P_i$ ($\sum_{i \in S} P_i \log_2 P_i > \log_2 P_i$) and $b_i > b_j$ for $i \in S'$ and $j \in S - S'$ iff E is increasing in time ($E \uparrow$) and D decreases in time ($D \downarrow$).

Interoperabilites cause Emergence

We consider four classes of agents based on interoperabilities, the abilities of agents to connect and effect each other in a decision network; *Influencers(INF)*, *Early Followers(EF)*, *Late Followers(LF)*, and *Isolated(ISO)*. The four classes exhibit descending rank of interoperabilities on the basis of their influences and ascending rank on the basis of their frequency in the decision network.

Let I^c represent interoperability between agents in different classes. There can be other interoperabilities in a system such as interoperability between pattern types. I generally shows the interoperabilities between properties of agents. We measure the interrelationship (R) between agents by the interoperability (I^c) matrix and their classification. $\min(I^c) = 0$ when two classes are independent (autonomic)

Table 3: Details of mechanisms of component

	$-\log_2 P_i > E$		$-\log_2 P_i < E$	
	$b_i > b_j$	$b_i < b_j$	$b_i > b_j$	$b_i < b_j$
$i \succ j$	$E \uparrow \wedge D \downarrow$	$E \downarrow \wedge D \uparrow$	$E \downarrow \wedge D \downarrow$	$E \uparrow \wedge D \uparrow$
$i \succcurlyeq j$	$E \uparrow \wedge D \downarrow$	$E \downarrow \wedge D \uparrow$	$E \downarrow \wedge D \downarrow$	$E \uparrow \wedge D \uparrow$
$i \succsim j$	$E \uparrow \wedge D \downarrow$ if (1), $D \uparrow$ if (2)	$E \downarrow \wedge D \uparrow$	$E \downarrow \wedge D \downarrow$ if (1), $D \uparrow$ if (2)	$E \uparrow \wedge D \uparrow$
$i \not\succcurlyeq j$	$E \uparrow \wedge D \downarrow$ if (1), $D \uparrow$ if (2)	$E \downarrow \wedge D \uparrow$	$E \downarrow \wedge D \downarrow$ if (1), $D \uparrow$ if (2)	$E \uparrow \wedge D \uparrow$

(1) $\sum X_i \int \sigma_i(w)dw > \sum X_j \int \sigma_j(w)dw$, (2) $\sum X_i \int \sigma_i(w)dw < \sum X_j \int \sigma_j(w)dw$.

and $\max(I^c) = 1$ when they follow each other (identical). We use Eq. 5 to calculate interrelationship of Agent υ with its neighbors (interrelated) in Pattern i.

$$R_{\upsilon i} = \frac{\sum_{\delta_\nu} \theta_{\upsilon\delta_\nu} . I^c_{\delta_\upsilon \delta_\nu} . X_{\delta_{\nu i}}}{\sum_{\delta_\nu} \sum_i X_{\delta_{\nu i}}}, \quad i = 1, ..., n, \upsilon = 1, ..., \sum_i X_i, \tag{5}$$

where, $I^c_{\delta_\upsilon \delta_\nu}$ is the interoperability of the agent in Class δ_υ with agent in Class δ_ν. $X_{\delta_{\nu i}}$ is the number of connected agents (neighbors) to Agent υ in Class δ_ν with Pattern i. *Average self-preference*, $0.5 \le \theta_{\upsilon\delta_\nu} \le 1$, lets two agents, from a same set of classification, have different interoperability with a specific agent.

To select an appropriate pattern for evolving, we use Eq. 6 here, $switch_{\upsilon t}$ is the patten that Agent υ chooses to evolve in time t.

$$switch_{\upsilon t} = arg_i\{\max(R_{\upsilon i})\}, \quad R_{\upsilon i} > \Upsilon_i, \quad \forall i, \tag{6}$$

where, Υ_i is the required support (motivation or profit) for switching i. To avoid evolving to similar patters we may use Eq. 7 instead of Eq. 6.

$$switch_{\upsilon t} = arg_i\{\max(R_{\upsilon i})\}, \quad R_{\upsilon i} > \Upsilon_i, \quad \forall i \neq \text{Pattern}(\upsilon). \tag{7}$$

Updates and adjustments cause Evolution

The probability that a system possesses attribute λ, such as willingness to adjust consumption pattern for a specific cost saving, is:

$$\phi(\lambda, t_0) = \begin{cases} 1, & \text{if} \quad \frac{M_\lambda(t)}{\sum_i X_i(t)} \ge \tau_\lambda, \quad \exists t_0 \in [0, t], \\ 0, & \text{if} \quad \frac{M_\lambda(t)}{\sum_i X_i(t)} < \tau_\lambda, \quad \forall t_0 \in [0, t], \end{cases} \tag{8}$$

where, τ_λ is the threshold for property λ and $M_\lambda(t)$ is the number of patterns which have the attribute λ.

Let $\Phi(t) = (\phi(\lambda, t); \lambda = 1, ..., \lambda_0)$ be a vector of 0 and 1's where, its λth position is 1 if $\phi(\lambda, t) = 1$. The system evolves when $\exists t' > t, \Phi(t) \in \Psi(\text{or } \Psi')$ & $\Phi(t') \in \Psi'(\text{or } \Psi)$. Where, $\Psi(t)$ is a predefined finite set of Φ's at time t and Ψ' is all other possible combinations of 0 and 1 for Φ's that are not in Ψ (i.e. complement of Ψ).

For example, in a power system agents are consumers of electricity. Each follows one of n different daily consumption patterns with probability P_i. These probabilities define entropy of features. A preferential attachment of a social network of consumer defines the interoperabilities I^c where, its edges depict the interrelationships R. The nodes of the network grow by fitness rate b_i where, the node degree distribution follows power law (scale-free network (Barabasi and Bonabeau 2003)). Statistical analysis of the system presents the initial b_i's that may change based on behavioral characteristics of consumers (they may be persuaded to migrate to other patterns by motivators such as dynamic pricing and attractiveness) and cause the emergence. Here, required data is gathered manually and simulated for future behaviors. Electricity regulators strive to balance the workload or reduce the peak time by defining evolution thresholds and sets in respond to demand fluctuations. They seek to control consumer behaviors by providing incentives and social education.

Conclusions and Future Research

The proposed framework enables us to model characteristics and behaviors of agents within a system and examine their correlations and responses to environmental changes. Our model allows studying hallmarks of CASs and helps us to analyze complexity in a system without complex modeling. This study can help us to define new measures for ECASs.

In the future, agent-based modeling and simulation of the dynamic system can support the mathematical modeling of this paper. We can improve the decision mechanisms in evolution by adding statistical or optimization learning algorithms. Moreover, we can study behavior of the system based on different complex decision network topologies (e.g. scale-free and single-scale networks). Some other characteristics of consumers such as irrationality (information, pricing, and communal benefit) or effect of externalities in their decisions may give closer results to the real cases. Here, we tried to minimize the dis-uniformity. However, controlling or predicting dis-uniformity is a more general objective that can be studied in the future under the presence of additional factors in the model such as price incentives.

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