An agent-based modeling optimization approach for understanding behavior of engineered complex adaptive systems

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A B S T R A C T

The objective of this study is to present a formal agent-based modeling (ABM) platform that enables managers to predict and partially control patterns of behaviors in certain engineered complex adaptive systems (ECASs). The approach integrates social networks, social science, complex systems, and diffusion theory into a consumer-based optimization and agent-based modeling (ABM) platform. Demonstrated on the U.S. electricity markets, ABM is integrated with normative and subjective decision behavior recommended by the U.S. Department of Energy (DOE) and Federal Energy Regulatory Commission (FERC). Furthermore, the modeling and solution methodology address shortcomings in previous ABM and Transactive Energy (TE) approaches and advances our ability to model and understand ECAS behaviors through computational intelligence. The mathematical approach is a non-convex consumer-based optimization model that is integrated with an ABM in a game environment.

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1. Introduction and literature review

Today's engineered complex adaptive systems (ECASs) are composed of many autonomous and heterogeneous components with myriad interrelationships. ECASs exhibit the inherent behaviors of natural complex adaptive systems (CASSs) but are designed for expressed purposes and include intrinsic design parameters and operational controls that can influence behavior. Nonetheless, autonomous agents interact with limited environmental information and without central control [5,76]. ECASs evolve to adapt to unforeseen dynamic conditions. Their highly dynamic and non-linear behaviors make them difficult to fully understand and thus to effectively design, operate, and maintain. The self-organizing components readjust themselves continuously and emerge new behaviors through interaction with other components and their environment. The individual agents adjust their decisions to optimize their objective functions but they may not be fully rational or knowledgeable and may have latent objectives and influences. Emergence in behaviors may also result from social network influences. This micro optimized emergence in the lower level causes optimized evolution in the higher level of the system. Our objective is to develop a descriptive platform and modeling approach that can be customized to understand the behavior of ECASs. In particular, we use the U.S. Electricity Markets as a target application in which complex social dynamics and engineered infrastructure interact to complicate complete understanding and ability to achieve societal goals.

The U.S. Electricity Markets behave as an ECAS (see Section 1.3 for references). Government and service providers desire to use price-based incentives to impact demand and achieve efficiency, reliability and sustainability. Most Demand Response (DR) programs have focused on large industries and business sectors (they mainly consider passive energy efficiency more than active DR options). Moving forward there is the potential to utilize smart technologies to include smaller consumers. Traditional studies focus on rational choice of economical drivers ignoring behavioral factors that may determine individual consumer demand elasticity to financial incentives. The current lack of supporting technology and knowledge of consumer behavior provide challenges for developing effective broad price-based DR programs. Challenges and needs to implement DR in accordance with Federal Energy Regulatory Commission (FERC) Order 745, March 2011 and Sections 1252(e)/(f) of the US Energy Policy Act of 2005 motivate this research and are considered in the modeling approach.
In our study an ECAS evolves on the basis of embedded behavior rules related to non-convex consumer-based optimization. A modeling approach is developed for general study of ECAs, behavioral-based demand response in the US power markets is used to demonstrate its applicability. Economic incentives motivate local consumers to adjust their pattern of demand usage. To study and analyze ECAS Refs. [48,49] defined emergence as “the capability of components of a system to do something or present a new behavior in interaction, and dependent to other components that they are unable to do or present individually”, evolution as “a process of resilience and agility in the whole system”, and adaptation as “the ability to learn and adjust to a new environment to promote their survival”. We will explain how to study these hallmarks of CAs in our agent-based simulation for Demand Response complex systems. Our research builds upon previous modeling approaches to resolve weaknesses of the current models (see comprehensive survey studies for agent-based electricity market models, tools, and simulation by Refs. [84,94,97]). We employ consumer interoperability in a social layer whereas previous research studied economic models in a business layer.

The key contributions of this study are:

- Developing a descriptive platform and integrated optimization and agent based simulation modeling approach that enables study of ECAS,
- Demonstrated application of the platform and modeling approach to understanding consumer social interactions in electricity demand response,
- Guidelines for improving effectiveness of economic incentives and targeted education in social networks,
- Understanding effects of the social network topologies for cascading behaviors.

The reminder of Section 1 provides background on electricity markets and ECAs and discusses the motivations of this study. Section 2 explains our integrated approach. Properties of the agents and their decision diagram are defined in Section 3.1. We depict the layers of the environment in Section 3.2, Section 4.1 details the logic of agent-based process and presents mathematical equations and definitions for the agent-based engine. Also, in Section 4.2 all decision variables and rules (defined in the previous sections) are integrated into an agent-based optimization model. Sections 5 and 6 show the simulation results. We define required variables to run the model and we analyze different scenarios. Various examples demonstrate the validity of our method in each section.

1.1. Motivation to study the US power system as an ECAS

The US electricity power system is one of the most complex systems ever invented [7]. The physical network consists of approximately 450,000 miles of high voltage lines and 146 Million ultimate customers [38,39]. Demand (nearly 3725 Billion Kilowatt-hours (kWh) in 2013) is increasing (expected to increase by 28 percent from 2011 to 2040) requiring capacity expansion, that along with its spatial-temporal stochasticity, stretches distribution constraints and impacts electricity markets. Additional features that motivate examining the US power system as an ECAS include:

- Time dependency of the network topologies [20], and
- Scale-free or single-scale feature of these networks - their node degree distribution follows a power-law or Gaussian distribution [85].

The US Federal Energy Regulatory Commission (FERC) formed Independent System Operators (ISOs) and Regional Transmission Organizations (RTOs) based on the Wholesale Power Market Platform [41] to coordinate, control, and monitor the operations of the US wholesale electrical systems. These entities manage electricity generation and transmission across geographic regions and balance supply and demand. ISOs/RTOs serve two-thirds of electricity consumers in the US based on Locational Marginal Price (LMP). This structure increases the complexity of the US wholesale electricity markets. As an illustration, Fig. 1 provides the LMP contour map of the Midcontinent Independent System Operators [72]. There is a huge gap between LMP values for two neighborhoods A and B (from –40USD in Point A to +150USD in Point B). This pattern may change totally in the next 5 min Fig. 2 depicts the LMP maps in different time intervals on Nov 23, 2015 (Fig. 2(a)–(d) show variation in short time intervals (15 min)).

Demand Response is defined by Ref. [37] as “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”. Pursuant to the Sections 1252 (e) and (f) of the US Energy Policy Act of 2005 (EPACT), the U.S. Department of Energy (DOE) has provided a report to Congress that identifies and quantifies DR benefits and makes recommendations for achieving them. The report shows that actual peak demand reduction was only 9,000 MW in 2004 while the potential demand response was 20,500 MW [37]. FERC issued Order 745 in 2011 to meet the Congressional direction and remove barriers to the participation of DR in organized wholesale electricity markets [42]. A list of questions that DR studies strive to answer includes:

- When (what day) is the best time to trigger a demand response event?
- What is the event window (start and finish time)?
- How much trigger is required?
- What type of events (rewards, penalties, larger and discrete, smaller and continuous) are more effective and efficient?
- Who are the event recipients? What is the schedule to receive their triggers?
- What percent of the recipients may answer to the triggers? What is their outcome (e.g. total saving)?

Electric power is generated from multiple sources of energy (coal, hydro, wind, solar, natural gas). Sources vary with respect to flexibility, startup times and operating costs thus increasing the complexity of dispatching and pricing electricity. Studies on behavior of consumers for the PJM Interconnection Regional Transmission Organization [88] show that small shifts in peak demand would have a large effect on savings (a 1% shift in peak demand would result in savings of $12.7 billion at the system). Large-scale social science field experiments by Ref. [11]; academic studies by Ref. [4]; and testimony by American Council for an Energy-Efficient Economy to Congress [2] suggest that social and behavioral programs can increase the efficiency of load management programs.

In the current electricity markets, demand response programs are managed by separate organizations (such as ISOs, utilities, aggregators, and retailers) that operate almost independently [45]. Due to the amount of new demands and challenges of customer...
controls, it is nearly impossible for utilities and independent system operators (ISOs) to manage and monitor the new complex system [8,89]. Moreover, Prosumers (i.e., consumers who also produce their own power from a range of different onsite generators) can significantly increase the complexity of the system [8].

Transactive energy (TE) is a relatively new concept (the first TE conference was held in 2013 in Portland, Oregon) that proposes a new approach to solve these complexities [1,45,90]. GridWise Architecture Council (GWAC), Transactive Energy Association (TEA), the Smart Grid Interoperability Panel (SGIP), and Pacific Northwest National Laboratory (PNNL) have discussed the concepts and standards of TE [45,69,70,78]. Ref. [45] defines TE as “A system of economic and control mechanisms that allows the dynamic balance of supply and demand across the entire electrical infrastructure using value as a key operational parameter”. TE facilitates collaboration and encourages cooperation between all elements of the power system. It tries to manage the electric power system via market-based incentives by taking advantages of two-way communications and intelligent communicating devices [45]. It is not clear what differentiates TE from smart Grid. While some experts believe that it just a Smart Grid application [8]; TE is an extension of the electricity markets to the end-use customers and the next step in development of demand response’’ [1]. Moreover, in TE concepts residential customers will have energy management systems (or a third party assistance) to make decision and create value [8]. TE plays a significant integrating role by providing communication capabilities between demand response programs [45].

Our model enables us to improve the ability of regulators and consumers to communicate and optimize consumption. We consider a technology-enabled system with smart meters and appliances where consumers can control their demand at all times in response to incentives (dynamic pricing). As electricity consumption is inelastic in short time frames, social education mechanisms are included to increase the effect of economic incentives. Our reward approach attempts to improve the effectiveness of triggers to motivate consumers to shift their demand. We show that combining social drives with economical incentives enables us to reduce and control the huge gap between potential load management and actual DR. We propose a more complex, less idealized multi-layered adaptive approach to show influences of combined social-economical incentives on behavioral-based DR programs. We seek to understand how to change consumption patterns of end-users and load aggregators to level demand by providing economical incentives and exploiting social networks.

1.2. Engineered complex systems and complex adaptive systems

Complex systems are classified by Ref. [67]. Four reports of the Defense R&D Canada-Valcartier [32–34] and Ref. [35] present a comprehensive survey to the study of complexity theory, chaos and complex systems. Mathematical modeling of CASs is fragmented and inapplicable because engineers and mathematicians focus on purposes and outcomes while complex systems are strongly characterized by emergence in behaviors of components and evolution in behaviors of a system. Refs. [13,14] mathematically studied the structure of complex systems and the interdependence of components. Difficulties in understanding emergence, abstract theoretical concepts, and incomplete applicable frameworks continue to present challenges in the study of CASs [36]. Despite this Ref. [77] shows that simple rules between components can describe an organized agent.

We are concerned with the interplay between the physical electricity generation and distribution network and the consumer social network. Ref. [6] studied structural properties of the electric power grid of Southern California and Ref. [91] considered the complex network of the New York electric power grid. Ref. [10] modeled evolutionary structure of population and components in social networks. Ref. [54] showed emergence of cooperative behavior by combining social network dynamics and stochastic learning. We are interested in how external control parameters can impact the behavior of the autonomous agents in the network and how that then translates into system behavior. Ref. [61] classified three developed approaches to mimic human complex decision behaviors. Refs. [59,60] employed engineering methodologies to represent such systems in complex environments. Ref. [62] considered information cascades in large social networks and investigate a large person-to-person recommendation network. Ref. [58] discussed probabilistic and game-theoretic models for flow of information or influence through social networks. Our study discusses the complex structure and behavior of a human decision-making system.
network itself and how components cooperate as a result of their connections through a network and in relationship with their environment. We include human decision making and show how our proposed framework encapsulates the previous models.

1.3. Agent-based modeling of engineered complex adaptive systems

Usually, game theoretical modelers only consider a limited number of components with often unrealistic assumptions. Traditional equilibrium models disregard strategic behaviors and learning of components [94]. Weaknesses of traditional modeling methods make agent-based modeling and simulation useful tools to study and analyze systems that exhibit emergent phenomena, nonlinear dynamics, and path-dependent behavior [27,65,66,86].

Recently, ABMs have been used to study the impact of new electricity technologies. Ref. [51] consider performance of a new technology versus an old technology and study the effects of a specific spatial externality (fashion effect). They analyzed the dynamics of technology diffusion among bounded rational agents with uncertainty by using ABM. An ABM for a market game is presented by Ref. [96] to evaluate the effects of government strategies on promoting new electricity technologies in complex systems involving human behavior. Ref. [9] used ABM to control consumer demands by supporting interaction between consumers in a diffusion mechanism. In another approach, advantages and disadvantages of optimization models and ABM for technological change in different energy systems is compared in Ref. [64].

The impact of the structure of a social network on the spread of innovations has been an actively researched issue. Ref. [73] considered competing alternatives when an agent adapts to a new behavior based on its neighbors. In their model the payoff for agents increases with the number of neighbors who adopt the same choice. Ref. [47] used dynamic pricing in modeling diffusion of innovations in a social network. Ref. [18] analyzed network topologies and communication links between innovator and follower market segments in the diffusion process. Ref. [80] compared agent-based and differential equation models and analyzed the effect of individual heterogeneity and network topologies in the dynamics of diffusion. Refs. [56,57] studied spread of an innovation or behavior based on word-of-mouth recommendations in social networks.

Agent-based modeling of complex adaptive electricity systems has been attempted by several countries and US national laboratories. Refs. [22–26] analyzed market power and price-formation of

![Fig. 2. Variation of LMP map of Midcontinent ISO by time.](image-url)
utilities and generators in the UK. Ref. [12] created a multi-agent model for the UK electricity generation market. In Germany Ref. [19] studied bidding strategies, and an agent-based German electricity market is presented by Ref. [83]. Refs. [46] and [28] presented an agent-based model for the complex adaptive system of interactions between human behaviors in markets, infrastructures and environment of Australia’s national electricity market by using the National Electricity Market Simulator (NEMSIM). In the US, the Agent-Based Modeling of Electricity Systems (AMES) is designed for computational study of wholesale power market [63,92]. Argonne National Laboratory developed the Electricity Market Complex Adaptive System (EMCAS) to analyze the possible impacts on the power system of various events [31,75]. 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 [16]. Honeywell Technology Center (HTC) constructed the Simulator for Electric Power Industry Agents (SEPIA) [95]. Pacific Northwest National Laboratory also studied power systems as complex adaptive systems [29]. These studies however have not considered social interactions or subjective behavior of consumers.

2. Multi-layered integrated approach

We propose a methodology that advances our ability to model and understand engineered complex adaptive system behaviors through computational intelligence. The development of this methodology has significant intrinsic merit as it will explore fundamental issues in multi-layered ECASs and presents new optimization actions. This ABM presents a platform and toolkit that creates a dynamic laboratory to study properties and behavior of consumer social interactions in the US Electricity Market demand response (DR) as an ECAS. This paper does not propose a specific power system platform for DR but studies the social interaction effects of complex adaptive consumers in electricity usage patterns. The concept of DR is used to define a value mechanism in the multi-objective optimization model and justify incentive/reward functions for agents to cooperate and change their behavior. We acknowledge that the modeling framework in this paper provides a first step. The goal of this paper is to provide a framework rather than a specific solution for any particular grid. Undoubtedly operators would need to consider their constraints in setting the incentives. Our framework provides a mechanism for those operators to model the DR of a set of proposed incentives.

We integrate concepts from social networks (e.g. friendship, scale-free and single-scale networks), social science (e.g. opinion exchange, media impact, and irrationality), complexity theory (e.g. emergent behavior and adaptation), diffusion theory (e.g. adaptability and innovativeness), and decision theory (e.g. utility) to build our comprehensive ABM. This model enables us to integrate optimization rules and build a comprehensive social layer to analyze and simulate details of social behaviors in ECASs. We justify our model by illustrating its applicability on the US power system.

In this study, a multi-layer descriptive modeling approach (Fig. 3) composed of conceptual behavior and fundamental entity aspects is considered as the whole system structure. This approach integrates layers by cross-layer effects, effect of stochastic events (e.g. system failure and extreme weather condition), and rules of standards and procedures. Usually, physical layer(s) model networks, their characteristics, and physical components [50]. In this layer effects of topology and structure of networks have been studied in the past by Refs. [18,47,73]. Decision/control layer(s) represent different business strategies, optimization models and rules for decision makers (e.g. regulators). Those models are used for short-term, mid-term, or long-term analysis. Previous modeling approaches such as AMES [63,92] are useful for modeling behaviors of this layer. Some models (e.g. EMCAS by Ref. [31] presents a more comprehensive view on different layers.

The GridWise Transactive Energy framework [45] depicts three layers of interoperability: physical (or cyber-physical) at the lower levels, information interoperability in the mid-levels, and business models (market structures, regulation, and policy) in the upper levels. One of the significant principles of Transactive Energy systems is to implement some form of highly coordinated self-
optimization [45]. Our proposed framework goes further than the current TE and other ABM studies as follows:

1. The TE framework suggests a likelihood of increasing interactions as social networks [45], but it does not define a social network in the TE framework. This paper considers the interactions between agents via a social network,

2. One of the most important TE challenges is to move from current centralized control systems to more distributed systems. "Distributed computing or control exists when the decentralized elements (that independently operate) explicitly cooperate to solve a common problem" [45]. This study proposes a mathematical model to examine the imputed cooperation of agents,

3. We need multi-objective optimizations to align the TE value discovery mechanism (an attribute of TE that establishes the economic or engineering value) of utilities, customers, and other operators [45]. In this study, a value-based optimization model is implemented to examine the cooperation, satisfaction, desirability, and other properties of the system components,

4. In TE concept, a free flow of information between parties allows them to enter into exchanges. In this concept Interoperability (an attribute of TE) is defined as enabled transaction through the exchange of information between transacting parties [8]. This study applies an explicit mathematical method to measure the interoperability and interrelationships,

5. Assigning value to the normal residential customers is tricky. Their values are usually defined through their choices and based on qualitative measures such as value comfort and satisfaction. In this study, the proposed dissatisfaction concept enables us to calculate and incorporate the non-economic aspects of values to the model.

In this study, Social/Swarm Layers(s) include the interrelationship between agents and their effects on each other. Also behavioral properties and attributes of decision makers are considered in this layer (see Section 3.2).

To show cascading of decisions from Decision/Control Layer(s) to Physical Layer(s), we detail the Social/Swarm Layer(s). This integration helps us depict emergence in behavioral patterns in the lower level of the system and their effects on evolution in the higher levels (e.g. predict the result of dynamic pricing and prizes in future). Moreover, we formulate a consumer-based optimization model and integrate it with the agent-based model. Then we include effects of externalities and subjective behaviors in the integrated agent-based optimization model. We study the effect strategies have on the decision/control and social/swarm layers. Useful managerial insights are derived from executing the model.

Electricity regulators adjust service attributes (e.g. price and reward functions) in response to demand fluctuations to motivate the consumer agent to cooperate in balancing workload. Consumer agents make decisions to maximize their quantitative and qualitative utilities. They change consumption patterns in response to incentives and to social education provided by the regulators. Based on the individual and total patterns of the electricity consumption, agents may receive individual and cooperation rewards. Moreover, they may have dissatisfaction to change their behavior (Section 4.1 presents details for calculating utilities, rewards, and dissatisfaction). We study cooperativeness or competition in the consumers game environment by embedding a non-convex consumer-based optimization model with the agent-based simulation (see Section 4.2). We study the behavior of consumers under different control and incentive strategies. Then, we include intrinsic environment and control factors to the model dynamics.

Instead of reducing nonlinear systems to a set of causal variables and error terms, our ABM shows 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, our ABM presents the evolution of outcomes as the result of the efforts of agents to achieve better fitness. This method allows the study and analysis of the complexities arising from individual actions and interactions that exist in the real world by bottom-up iterative design methodologies. Applying this integrated agent-based optimization model has the following benefits for the US power system and may lead 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.

3. Agent-based structure

This section presents an overview of agents’ properties and their environment. We present more details and mathematical modeling of the framework in Section 4. Outcomes of running the simulation are discussed in Section 5.

3.1. Decision makers/agents

1- Pattern of Consumption: Consider System (e.g. a power system) comprised of a large number of components (e.g. consumer agents). We study the individual electricity consumption $C(w)$ of these agents which changes dynamically during a period of length $w_0$. For example, $C(w),0 \leq w \leq 24$, is the profile of daily consumptions when $w_0 = 24$ hours. We assume there are $q$, $q = 1,\ldots, T$ equal discrete periods and that $C_i(w)$ may differ at each period. As an illustration, to show consumption of electricity for a year, $w$ covers the 24 h of consumption at each day while $q = 1,\ldots, 365$. Behaviors of components are grouped into classes based on similar consumption pattern. Assume there are $n$ defined classes of patterns and each component follows one pattern at period $q$. We use $X^q_i, i = 1,\ldots, n$ to show the number of components that follow class $i$. Here, $Q^q = \sum X^q_i$ is the total number of components in the system at period $q$. $C^q_i(w)$ presents a profile of daily consumption at period $q$ for consumer that follows pattern $i$ $(C^q_i(w)$ is the consumption of electricity at time $w$ for pattern $i$ in period $q$).

2- Properties of Agents: Agents have the capability to present new behaviors by interaction and dependent to other agents. They can switch to new patterns and change their attributes based on their current properties and neighborhood relationships. We represent the influence on an agent from another agent by interoperability (will be defined mathematically in the next section). We initiate a social network of consumer agents where $X(0)$ is the initial size of the population for each pattern and the population of each pattern $(X_i(1) = 1,\ldots,n)$ can grow with growth rate, $b$, exponentially. Agents may switch from one pattern to another based on the attributes of the patterns (namely; price, convenience, and glamour) or through influences of these in their social network. Price defines the total cost of consumption in a 24 h cycle time for
the related pattern. Convenience shows how fast and easy consumers can make a decision to switch to this pattern. Glamour shows the effects of advertisement or other fashion attributes of the patterns. These micro interrelationships make new networks and update the structure of the population in the macro level of the system.

2- Influences on Agent Decisions: Fig. 4 shows how agents are influenced in the system. Ovals present uncertain variables. Rectangles show the variables that the agents have the power to modify or select. Hexagons are measurable outcomes. Arcs denote direct influences. Dashed arcs indicate there are some influences; however, the values can be calculated from other variables with direct influences. Agents consume electricity based on the environment conditions (e.g. seasonal weather conditions and time of the day) and consumption attributes (e.g. price of electricity consumption and advertisements). This consumption shapes their pattern of behaviors. The entropy of the system, \( E = - \sum P_i \log P_i \), is defined by the frequency of these patterns and the interrelationships between the agents (i.e. emergent behavior of agents, interoperabilities, and willingness to effect or follow each other). This entropy of the patterns in a system, yields the dis-uniformity (Eq. (4)) of the whole system. Cooperation reward (Eq. (15)) can be measured based on the regulator’s decisions. Consumers measure their profit (Eq. (14)) on the bases of the cooperation reward, their individual rewards, their dissatisfaction, and qualitative utilities. Individual rewards (Eq. (16)) and dissatisfaction (Eq. (17)) are calculated based on the patterns of individual behavior. Qualitative utilities (Eq. (13)) are functions of the consumption attributes. This total profit leads agents to change their consumption in the cooperative game model to adapt to the new environment.

We can characterize the agents as follows (they will be discussed and defined by details in the next sections):

- Each agent runs a pattern that has three attributes (price, convenience, and glamour),
- Agents connect to each other based on a complex network,
- An agent has desirability coefficients and importance weights for each attribute,
- Agents belong to interoperability classes based on their node degrees,
- An agent (partially or fully) optimizes its profits based on optimization rules in cooperation with other agents,

3.2. Environment/patches

Fig. 5(a)–(c) present an overview of a three-layer image of our modeling study. The Decision/Control Layer (Fig. 5(a)) includes strategies (e.g. dynamic pricing), optimizing (e.g. maximum profits and peak reduction), plans (e.g. new generators), investments (transmission and distribution infrastructure), and information sharing (e.g. communicate energy information). In the US energy system Independent System Operators (ISOs) and Regional Transmission Organizations (RTOs) work in this layer of the complex system.

The Social/Swarm Layer (Fig. 5(b)) considers interrelationships between agents and preferences. We can consider bounded rationality for agents and externalities (e.g. fashion effects) in this layer. Non-physical attributes of agents (e.g. glamour) and their utility function can be studied and analyzed here. We will discuss how the behavior of agents as a group emerges in this layer and converges to a steady pattern. Learning algorithms (e.g. reinforcement learning) and adaptation scenarios can be considered in this layer.

The Physical Layer (Fig. 5(c)) includes features, mechanism of components of the system, and their physical network. In the energy system example this layer includes generators (e.g. main power plant, wind forms, solar panels, and small generators), distributors and transmission, and consumers (e.g. homes, businesses, and industries). The topology of networks is considered in this layer.

This paper focuses on the social layer and does not focus on a specific architecture or a detailed physical layer. Similarly, the TE framework is not suggested as an architecture or the standards for TE [8]. These works should be done by a team of expert power system architects to represent the design of a specific case of a power system. For more information review the ABM and TE.
The Social/Swarm layer helps us to cascade effects of the Decision/Control layer(s) to the Physical layer(s) by modeling the emergence and adaptation of the whole swarm. The topology of connectedness and protocols for interaction in the network are important properties of the network for our study. The topology of interactions defines who is, or could be, connected to whom. The protocols of interactions are the mechanisms of the dynamics of the interactions. Both specify the local information accessible to an agent. The structure of the network (e.g., scale-free or single-scale properties) helps us to calculate the class of interoperability for each agent and find its influencer nodes. We assign the class of an agent based on the size of the network and the degree of the node (see the next section for mathematical details). Also, we consider the pattern of behavior for each consumer. The distribution of patterns of behaviors and the way the agents are seeded with patterns are important. We present the value of interoperability between two agents as the weights of the edges. In summary, three parts of the network are used in our agent-based modeling (they are mathematically defined in the next section):

1. Patterns of nodes (consumer agents),
2. Degree of agents that is related to the structure of the network,
3. Weights of edges that show the interoperability of agents.

The social network $G$ between agents with preferential attachment and growth can be represented by a scale-free network [47,73,87,91]. $|E(G)|$ is the set of links in the social network $G$. The nodes of the network depict autonomous consumer agents while the edges symbolize the influences or interoperability between the agents. The node degree distribution of the network follows a power law i.e., the probability a node has $k$ edges is $ck^{-\delta}$ where, $c$ is a normalization constant and $\delta$ defines the shape of the distribution [3,15]. We will relax this assumption to study single-scale behavior of a Gaussian network later. The size of the network may grow by period while its scale-free/single-scale characteristic remains valid.

### 4. Agent-based optimization engine

This section presents the detail procedure of decision rules to show how agents optimize their actions and change their behaviors.

#### 4.1. Process Overview and scheduling

Fig. 6 shows the logical flowchart of the agent-based process and its scheduling. The flowchart includes three main sections: setup, switch, and optimize. Switch and optimize together regulate the dynamic behavior of the network initialized in setup.

1. **Setup section** initiates the scale-free network of interrelated consumers and seeds them with the patterns of consumption. Assume initially that agents are independent (this assumption will be relaxed later to induce complex behavior). Population of pattern $i$ ($X_i; i = 1, \ldots, n$) changes exponentially (Eq. (1)) with growth rate $b_i$ at period $q$, $q = 1, \ldots, T$. We need this equation to setup the initial social network and its growth rule. We will incorporate the complex topology of the influences and switching rules later in this section. Complex Entropy of the system is analyzed in Section 6. Note a complex system is comprised of a large number of components, so $X_i$ is integer (with a good approximation) in all periods.

\[
X_i^{(q+1)} = b_i X_i^q + X_i^q.
\]  

(1)

Note that generally $b_i$ can be negative or positive. For pattern probability $P_i = X_i / \sum X_i$ the growth of entropy follows Eq. (2).

\[
E^{(q+1)} - E^q = \sum_{i=1}^n b_i P_i \left( \sum_{i=1}^n P_i \log_2 P_i - \log_2 P_i \right). 
\]  

(2)

Here, at each time increment, new agents create $\theta$ connections with previous agents based on the scale-free property where $\theta$ is a random number between 1 and $\theta_{\text{max}}$. Here $\theta_{\text{max}}$ defines the max link generation. We assign desirability coefficients and attribute weights to the agents that will be used to compute optimization decisions (to be formally defined later).
We measure the agents’ level of cooperation by the dis-uniformity of aggregated pattern consumption at period $q$. The dis-uniformity of pattern $i$ is shown in Eq. (3). Recall $C_q^i(w)$ is the consumption of electricity at time $w$ for pattern $i$ in period $q$. Let $C_q^i = \int_0^{w_0} C_q^i(w) \, dw/w_0$ be the daily time average consumption of pattern $i$ at period $q$. The dis-uniformity of pattern $i$ in period $q$ is:

$$D_q^i = \int_0^{w_0} \left( C_q^i(w) - \bar{C}_q^i \right)^2 \, dw. \quad i = 1, \ldots, n, \quad q = 1, \ldots, T. \quad (3)$$

The dis-uniformity of a pattern is the mean square deviation between the current state of an agent and the goal state (the average daily consumption) (see Refs. [48,49] for detailed discussion on its relations to the entropy).

To establish a value mechanism to motivate the decision makers (consumer agents) to cooperate and achieve in such a way that the aggregate consumption in each period is uniform over time, we seek to minimize the total dis-uniformity, Eq. (4). This mechanism helps us on better load management and peak reduction. The other possible values based on the attributes of a consumption pattern, agent preferences, satisfactions, and comfort will be added to a multi-objective optimization model later in this paper. Used to address “what if” scenarios, the model allows predictability of demand response which in turn can facilitated determining resource adequacy.

$$D^i = \int_0^{w_0} \left( \frac{1}{\sum_{i-1}^{n} \bar{X}_q^i} \sum_{i=1}^{n} \left( C_q^i(w) - \bar{C}_q^i \right) X_q^i \right)^2 \, dw. \quad (4)$$

The total Dis-uniformity, Eq. (4), could be reduced by incentives that change one or more profiles or rearrange probability of
patterns. We will show interactions between agents and their interoperability effects on dis-uniformity of the system.

2- Switching section defines a set of rules for finding a switching target based on interoperability of agents. We define four sets of classified interoperability for the social layer population on the basis of the network protocol. This classification shows the agent’s ability to connect and effect each other where, \( \delta_i \) shows the class of agent \( u, v = 1, \ldots, \sum_{j=1}^n X_j \). Influencers(INF) have the highest number of connection links (interoperability). They maintain central positions in the social network and their numbers are small. Based on behavioral profiles, we classify agents by type INF, EF, LF, and ISL. Early Followers(EF) are more localized and have less interoperability compared to the influencers. Late Followers(LF) are classified between the Early Followers and Isolated categories. Isolated(ISL) have low interoperability. They do not have a big influence on other individuals and are insensitive to others. The idea of this classification is similar to the term innovativeness categories in diffusion theory by Ref. [81]. However, innovativeness categories consider speed of adaptation while we consider influences and interoperability in a network.

The network node degree distribution follows a scale-free power-law and the node degrees depend on the network size. To measure the interoperability classification based on this protocol we need to linearize the power-law functions. We use Eq. (5) as the linearization function and Eq. (7) shows how the power-law functions are linearized for each classification.

\[
\text{Lin}(\alpha, \beta) = \alpha \cdot \ln(|E(G)|) - \beta, \tag{5}
\]

where,

\[
\delta_i \in \{ \text{INF}, \text{EF}, \text{LF}, \text{ISO} \}.
\]

\[
\alpha_{\text{INF}} > \alpha_{\text{EF}} > \alpha_{\text{LF}} > \alpha_{\text{ISO}},
\]

\[
\beta_{\text{INF}} > \beta_{\text{EF}} > \beta_{\text{LF}} > \beta_{\text{ISO}}.
\]

and, \(|E(G)|\) shows the number of links in the social network \( G \) (total number of interoperability links). All agents follow a similar network topology in the network \( G \). Deg, is the degree of agent \( v \) in the network i.e. the number of interoperability connections that each consumer makes in the system.

\[
\delta_i = \begin{cases} \text{INF}, & \text{if } \text{Deg}, \geq \ln(\alpha_{\text{INF}}, \beta_{\text{INF}}), \\ \text{EF}, & \text{if } \ln(\alpha_{\text{EF}}, \beta_{\text{EF}}) \leq \text{Deg}, < \ln(\alpha_{\text{INF}}, \beta_{\text{INF}}), \\ \text{LF}, & \text{if } \ln(\alpha_{\text{LF}}, \beta_{\text{LF}}) \leq \text{Deg}, < \ln(\alpha_{\text{EF}}, \beta_{\text{EF}}), \\ \text{ISL}, & \text{otherwise}. \end{cases} \tag{7}
\]

In summary, to classify the agents we chose \( z \) and \( \beta \). Then the size of the network and the degree of the node determine the agent classes. We will use these classes to assign interoperability between agents and calculate their interrelationship.

For agent \( v \) consider all other agents that are connected to \( v \). The influence on agent \( v \) from agent \( z \) is based partly on the classes of the two agents. Let \( \delta_i \) represent interoperability between classes of agents. Here, \( \delta_i \) is a monotonic function of the influence that an agent of Class \( \delta_j \) has on an agent of Class \( \delta_i \). Interoperability is a positive number with maximum of one where, \( \delta_i = 0 \) shows autonomic (independent) class of agents and \( \delta_i = 1 \) when they follow each other (identical). Table 1 shows an example of an interoperability classification matrix. Section 5 provides justification for values in this table.

Self-preference \( \theta_{uv} \), lets agents vary their individual interoperability i.e. it lets two agents have different interoperability with a specific agent even if all three of them are in the same set of classification. The interoperability matrix defines a maximum possible value for all pairs of classification sets and \( 0.5 \leq \theta_{uv} \leq 1 \) may vary this value to half of its maximum. \( \theta_{uv} = 1 \) agent \( u \) does not have any self-preference and follows the interoperability matrix. Note if \( \theta_{uv} = 0 \), the model will be modified to a system without the network. To simplify the formulation we use \( \theta_{uv} = \sum_{i=1}^{n} \theta_{uvi} / X_{u\theta_i} \), average self-preference, in Eq. (8). For example, assume consumer 1 has two neighbors (consumers 2 and 3) and all three of them are INF. Based on Table 1, consumer 1 can have maximum interoperability 0.8 with both neighbors. However she/he may has less willingness to be affected by consumer 3. Then consumer 1 reduces its interoperability to 0.4 by selecting self-preference equal to 0.5 (See more examples in Fig. 7(a) and (b)).

The interrelationship \( R_i \), between agents will be assigned based on the interoperability, \( P_i \), and their classification. Let \( X_{uv} \) be the number of connected agents (neighbors) to agent \( u \) in class \( \delta_j \) with pattern \( i \). To calculate interrelationship of agent \( u \) with its neighbors in pattern \( i \) we used Eq. (8),

\[
R_{ui} = \frac{\sum_{j=1}^{n} \theta_{uji} \cdot P_{uj}}{\sum_{j=1}^{n} P_{uj}}, \quad i = 1, \ldots, n, \text{ } v = 1, \ldots, Q. \tag{8}
\]

where, \( P_{uj} \) is the interoperability of the agent in class \( \delta_j \) with agent in class \( \delta_i \). \( \theta_{uji} \) is the pattern that agent \( u \) chooses as the switching target at period \( t \). The agents have two ways to select their targets. Eq. (9) allows the agent to consider the strongest or top two alternatives held by connected agents where, \( \text{switch}^{q}_{i} \) is the pattern that agent \( u \) chooses as the switching target at period \( t \). Each period, such as a day, agents potentially react to stimuli and may change their patterns. To select an appropriate pattern as a switching target, we use Eq. (9) or Eq. (10) allowing the agent to consider the strongest or top two alternatives held by connected agents where, \( \text{switch}^{q}_{i} \) is the pattern that agent \( u \) chooses as the switching target at period \( t \). The agents have two ways to select their targets. Eq. (9) allows the agent to compare its objective with the objective of its highest weighted interrelationship neighbor. Here the switching target of agent \( u \) is the pattern of an interconnected agent with the highest interrelationship in its neighborhood. The decision to switch requires overcoming the inertia of the current set point. To consider the agent tendency to stay in her current pattern, we define an awareness-threshold \( r_i \) that must be overcome to switch. Thus, \( R_{ui} = \frac{\theta_{ui} + Y_{i}}{Y_{i}} \), if \( i = \text{Pattern}(v) \), where \( \theta_{ui} \) is her current interrelationship.

\[
\text{switch}^{q}_{i} = \arg\{\max(R_{ui})\}, \quad \forall i. \tag{9}
\]

To avoid similar patterns when the agent with the highest interrelationship has the same pattern with the target, we may use Eq. (10) to let agents look at the second highest interrelationship.

\[
\text{switch}^{q}_{i} = \arg\{\max(R_{ui})\}, \quad \forall i \neq \text{Pattern}(v). \tag{10}
\]

Example 1: Fig. 7(a) presents an example for calculating interrelationships. Assume consumer \( u \) is an agent trying to decide whether to switch her consumption pattern. Agent \( v \) is an influencer agent, INF and six other agents are connected to this agent. Two of them follow pattern \( i \) (1 EF, 1 LF), three of them follow pattern \( j \) (1 INF, 1 EF, 1 LF), and one of them follows pattern \( k \) (INF) at this time. Assume the awareness-threshold \( Y_{i} = 0 \) and the agent \( u \) does not have any self-preference i.e., \( \theta_{ui} = 1 \). Then \( R_{ui} = 0.6 - 0.4 = 0.2 \), \( R_{ui} = 0.6 + 0.4 = 0.3 \) and \( R_{vj} = 0.8/6 = 0.13 \). Hence, if agent \( u \) has the pattern \( i \) the switching target \( \text{switch}^{q}_{i} \) is from \( i \) of (10) and \( \text{switch}^{q}_{i} = j \) otherwise.
Example 2: Fig. 7(b) continues Example 1 by adding a self-preference to the agent $v$ for one of its neighbors (underlined number in the arc). This means agent $v$ prefers to weigh the interoperability of the EF class of pattern $i$ by half ($\theta_{vi} = 0.5$). We calculate $R_{vi} = 0.5 \times 0.6 + 0.4/6 = 0.12$ changing switch$^q = k$ if we use Eq. (10) and Pattern($v$) = $j$.

Note the ordering of influence does not matter as the agents influence each other and make decisions at the same time (same iteration) then change their behavior in the next iteration. This ability is built into the agent-based model.

3- Optimizing section: once a target pattern is defined, the agent has to decide whether to keep her current pattern or to switch based on the patterns’ utility functions, rewards, and dissatisfactions. The total utility value of a pattern is a weighted average of the desirability score $\Omega_{gs}$ that is a number between 0 and 1 for each attribute [74]. Recall that the attributes are price, convenience, and glamour. Here, $\Omega_{gs}$ shows the desirability score of agent $v$ for attribute $s$. When the agents target the maximum value of an attribute (e.g. glamour), to calculate the desirability, we use Eq. (11) where $y$ shows the value of the attribute and $L$ and $U$ are its lower and upper bound in Fig. 8(a). We apply Eq. (12) when the target is a minimum value, Fig. 8(b) (e.g. time to make decisions or cost of changing behaviors). The Desirability coefficient $\gamma_{ts}$ parameterize the desirability score $\Omega_{gs}$. Desirability functions showing $(\gamma < 0)$ characterizes risk-averse agents and $(\gamma > 0)$ characterizes risk-seeking agents if the agent targets a maximum and vice versa if the agent targets a minimum.

$$\Omega_{gs} = \begin{cases} 1 - \exp \left( \gamma_{ts} \frac{y_s - L_s}{U_s - L_s} \right) & \text{if } \gamma_{ts} \neq 0, \ v = 1, \ldots, Q, s = 1, 2, 3, \\ \frac{y_s - L_s}{U_s - L_s} & \text{if } \gamma_{ts} = 0, \ v = 1, \ldots, Q, s = 1, 2, 3. \end{cases}$$

$$\Omega_{gs} = \begin{cases} 1 - \exp \left( \gamma_{ts} \frac{U_s - y_s}{U_s - L_s} \right) & \text{if } \gamma_{ts} \neq 0, \ v = 1, \ldots, Q, s = 1, 2, 3, \\ \frac{U_s - y_s}{U_s - L_s} & \text{if } \gamma_{ts} = 0, \ v = 1, \ldots, Q, s = 1, 2, 3. \end{cases}$$

The Utility Value $U_v$, is the weighted average of the desirability scores of its pattern attributes. Agents can assign their own importance weight $W_{gs}$, to different attributes to have individual value functions (Eq. (13)).

$$U_v = \frac{\sum_s W_{gs} \Omega_{gs}}{\sum_s W_{gs}} \quad v = 1, \ldots, Q, s = 1, 2, 3.$$
patterns. The Cooperation reward $R_c$ is a function of the total dis-uniformity. An agent may receive this reward without any switching when their current pattern cooperates with others to reduce the dis-uniformity i.e. cooperation reward will be payed by the central authority to all agents based on the total dis-uniformity that they create. The Individual reward $R_i$, reflects the controllers individual rewards to the agent based on the contribution of the agent pattern to the central objectives. An agent will receive more individual reward when they choose to change their pattern of behavior in the way that minimizes their dis-uniformity. Dissatisfaction $\phi$ is the only variable that has a negative effect on the decisions. Dissatisfaction will be measured based on the amount of difference between new and old pattern of each agent. The more each agent changes its pattern the more dissatisfaction with its decision (see Section 4.2 for the formulations).

At the end of each period the pattern of the agents are updated as follows:

1. In a growing network ( $\exists b_i > 1$ ), the new network expands from the old one.
2. Agent classes are redefined based on the network topology.
3. Interrelationships are updated.
4. A target pattern will be selected based on the chosen switching rule.
5. The agent applies a decision rule based on value of perceived choices.

4.2. Decision rules

In the previous section we described how an agent determines the utility value of a possible switching target. A consumer-based optimization will be executed in order to determine if switching actually occurs. Decision makers (consumer agents) desire to maximize their total reward $\pi_i$. The total reward is a normalized sum of the cooperation reward $R_c$, the individual reward $R_i$, the utility value $U_i$, and dissatisfaction $\phi$ of the agents. The consumer-based optimization compares the anticipated total reward $\pi^{q+1}_i (C_i^q (w), C_{\text{switch}}^q (w))$ with the reward obtained continuing the current pattern, $\pi^q_i (C_i^q (w), C_{\text{switch}}^q (w))$. If $\pi^{q+1}_i (C_i^q (w), C_{\text{switch}}^q (w)) > \pi^q_i (C_i^q (w), C_{\text{switch}}^q (w))$, the agent switches her pattern to the pattern given by the possible switch in the period $q + 1$. A general model for agent $\nu$ at period $q$ would be,

$$\pi^q_\nu = k_\nu R^q_\nu + k_\nu C^q_\nu + k_\nu U^q_\nu - k_\nu \phi^q_\nu, \quad (14)$$

where, $U^q_\nu$ is defined by Eq (13) and

$$R^q_\nu = f_0(D^q_\nu), \quad \forall \nu, q, \quad (15)$$

$$C^q_\nu = f_0(D^q_\nu), \quad \forall \nu, q, \quad (16)$$

$$\phi^q_\nu = f_2(C_i^q (w), C_{\text{switch}}^q (w)), \quad \forall \nu, q, w. \quad (17)$$

The maximization is to be taken relative to the decision that agent $\nu$ can make in period $q$. To be specific, we choose the cooperation reward $R^q_c$ a decreasing exponential function of the total dis-uniformity (defined in Eq (4)) at period $q$, $f_0(D^q_\nu) = \lambda_0 e^{D^q_\nu/\mu_0}$, and the individual rewards $R^q_i$ a decreasing exponential function of the individual dis-uniformity (Eq. (3)) of each agent at period $q$, $f_0(D^q_\nu) = \lambda_0 e^{D^q_\nu/\mu_0}$. Values of $\lambda_0$, $\lambda_0$, $\mu_0$, and $\mu_{\phi}$ are constants and will be assigned later in this study. We choose the dissatisfaction $\phi^q_\nu$ to be a logarithmic function of the differences between current and previous pattern of consumption behavior, $f_2(C_i^q (w), C_{\text{switch}}^q (w)) = \ln(\int_0^{\infty} C_i^q (w) - C_{\text{switch}}^q (w) \, dw) / \lambda_2$. The value of $\lambda_2$ will be assigned later in this study. Note that this presents the agents decision model. Above this sits the master problem of the controlling entity who sets prices and rewards in order to induce desired behavior (consumption).

4.3. Termination rules

The simulation continues the flow described in Fig. 6 until one of the following termination rules apply:

- The patterns do not change any more,
- A maximal period (simulation time) has been reached.

5. Agent-based simulation and specifying the parameters

Here is an example to show how our integrated Agent-based optimization model simulates and analyzes the emergent behavior of consumption patterns. This study enables the electricity regulators to examine the effect of social interaction topologies with more realistic cognitive behaviors and improves the efficiency and effectiveness of demand response and peak reduction programs via behavioral-based incentives (e.g. social education and advertisement).

To illustrate the dynamic behavior of our system we assume three patterns of consumption (see Refs. [21,44,52,53,55,79] for justification and examples). Fig. 9 shows the behavior of those patterns in 24 h.

Table 2 presents the variables for running the model. Convenience varies between 2 and 5 indicating relative time or effort required to change to a pattern. Glamour is a qualitative variable with higher values implying more fashionable or advertised patterns.

Consumers are autonomous and receive $\gamma_i$, $W_i$, and $\theta_{\text{incl}}$ identically from sampling random Normal and Uniform distributions ignoring negative samples. To classify the consumer agents based on their interrelationships, we set $\alpha_{\text{inf}} = 4.5$, $\alpha_{\text{af}} = 2.5$, $\alpha_{\text{lf}} = 1.5$, $\alpha_{\text{lf}} = 17$, $\beta_{\text{ef}} = 9$, and $\beta_{\text{ef}} = 5$. Moreover, we assume $f_0(D^q_\nu) = 100 e^{D^q_\nu/\mu_0}$, $f_0(D^q_\nu) = 100 e^{D^q_\nu/\mu_0}$, and $f_2(C_i^q (w), C_{\text{switch}}^q (w)) = \ln(\int_0^{\infty} C_i^q (w) - C_{\text{switch}}^q (w) \, dw) / 2$. These parameters are defined to provide proper scaling and their impetus discussed in previous sections.
To define interoperability between agents we use the results of empirical studies on spread of happiness [43], dynamics of smoking [30], and formal/informal influence in adoption [93]. Refs. [43] and [30] classify individuals in large social networks based on their influence and study probability of changing behaviors (smoking habits and happiness) in agents when their connected agents adopt to a new behavior. Based on both studies we conclude that the probability to influence a participant in the same class is approximately 50%, 35%, 25%, and 10% for the classes of close friend, friend, spouse, and colleague respectively [93]. showed that authority structure like the one between managers and workers will add to or subtract to the influences determined in the previous studies. Based on these studies we choose the interoperability between the two classes of agents as shown in Table 3. These interoperabilities are selected for consistency with the finding of the three mentioned comprehensive studies but are not uniquely determined.

### 6. Analyzing behaviors

We study the behavior of the integrated agent-based optimization system under a variety of different circumstances. We examine how the agents' tendency to stay on their own pattern (awareness-threshold) effects the distribution of entropy of the system. We define a baseline awareness-threshold based on previous studies. Then we show how the regulators can improve the effect of a social network. Also we build more realistic results by considering limited rationality in cognitive capabilities of agents. Finally, we show the effect of saturated friendship behavior in the system.

#### 6.1. The effect of the awareness-threshold

To study behavior of the system we run the model with the default values in Table 2 while we modify the awareness-threshold \( r \) from 0.00 to 0.32 in 0.02 increments (for larger thresholds the system does not converge in 400 time periods). Fig. 10 shows the results of 300 runs. This figure shows the distribution of the time to converge as a function of awareness-threshold \( r \). This time is defined as the time when the entropy of the system is less than 0.3364 i.e. when at least 95% of agents converge to a pattern (here is Pattern \( i \)).

Fig. 11 depicts a vertical slice from Fig. 10. We see how the distribution of convergence to pattern \( i \) shifts from left to right by increasing the awareness-threshold \( r \). The convergence time increases by increasing the awareness-threshold i.e. the agents have more tendency to stay in their current pattern and converge slower.

Fig. 12 compares the average entropy of systems with different awareness-thresholds. Larger awareness-thresholds cause higher entropy in the system because the system converges slower and has more agent diversity by period. For very large awareness-thresholds (e.g. 0.3), the system does not converge in 400 periods. At the beginning of the simulation, the entropy may increase because the agents may start to switch from a high populated pattern to a low populated one. These results match with Theorem II and Corollary II in Ref. [49] where pattern \( i \) positively dominates patterns \( j \) and \( k (i \neq j \text{ and } i \neq k) \). Here, the objective is to minimize the total dis-uniformity in time (D1) so based on Theorem II1 entropy is increasing in time (\( E1 \)) as long as \( E < -\log bp \), and based on Theorem II2 entropy is decreasing in time (\( E1 \)) when \( E > -\log bp \). For more details and proofs see Ref. [49].

#### 6.2. Establishing a BaseLine

As a baseline we use the current system that has small interaction (almost zero) and we intend to increase the interactions. Interoperability in our system shows improving the interaction due to control decisions. It has been observed that only 5% of end users are currently empowered to react to the real-time or day-ahead locational marginal price (LMP) and participate in DR Programs [40]. In order to calibrate our agent-based simulations, we will determine an awareness-threshold that generates a change in pattern over time that is as close as possible to a simulation without a network and 5% participation rate. We quantify the closeness of two simulations by registering the average percentage of population \( P_{1i}^{(1)} \) and \( P_{2i}^{(2)} \) of pattern \( i \) in the system as function of time period \( q \). The difference \( H \) (Eq. (18)) is the absolute sum of difference pattern over time:

\[
H = \sum_{i} \sum_{q} \left| P_{1i}^{(1)} - P_{2i}^{(2)} \right| \quad i = 1, 2, 3; \quad q = 1, \ldots, 400. \tag{18}
\]

Fig. 13 shows the total difference \( H \) between an agent-based simulation without network (5% participation) and an agent-based simulation with a social network as a function of the awareness-thresholds.

Based on Fig. 13 awareness-threshold between 0.08 and 0.14 yields the most similar behavior with current systems without networks. For example Fig. 14 compares the emergence in the pattern of behavior in the first ten runs for awareness-threshold = 0.1 and 0.3. The system converges after 160 time

<table>
<thead>
<tr>
<th>Parameter</th>
<th>Variable</th>
<th>Range</th>
<th>Units</th>
<th>Default</th>
<th>Area</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Initial Population</td>
<td>( v = 1, \ldots, \Sigma_{X} )</td>
<td>100–inf</td>
<td># of consumers</td>
<td>500</td>
<td>E</td>
<td></td>
</tr>
<tr>
<td>Initial patterns</td>
<td>( X_{i} / \Sigma_{X} i = 1, 2, 3 )</td>
<td>0 to 1</td>
<td>% of total population</td>
<td>0.15, 0.65, 0.20</td>
<td>E</td>
<td></td>
</tr>
<tr>
<td>Growth rate</td>
<td>( b_{a} i = 1, 2, 3 )</td>
<td>0 to 1</td>
<td>% of pattern population</td>
<td>0, 0, 0</td>
<td>E</td>
<td></td>
</tr>
<tr>
<td>Max link generation</td>
<td>( \Omega_{max} )</td>
<td>1 to 10</td>
<td>number</td>
<td>1</td>
<td>E</td>
<td></td>
</tr>
<tr>
<td>Price</td>
<td>( S_{t} )</td>
<td>3–8</td>
<td>Currency (cents/KWh)</td>
<td>5, 5, 5</td>
<td>C</td>
<td></td>
</tr>
<tr>
<td>Convenience</td>
<td>( S_{c} )</td>
<td>2–5</td>
<td>Qualitative</td>
<td>4, 4, 4</td>
<td>C</td>
<td></td>
</tr>
<tr>
<td>Glamour</td>
<td>( S_{G} )</td>
<td>1–10</td>
<td>Qualitative</td>
<td>3, 3, 3</td>
<td>C</td>
<td></td>
</tr>
<tr>
<td>Desirability coefficient</td>
<td>( \gamma_{c} )</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>A</td>
<td></td>
</tr>
<tr>
<td>Attribute weight</td>
<td>( W_{c} )</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>A</td>
<td></td>
</tr>
<tr>
<td>Average self-preference</td>
<td>( \theta_{d} )</td>
<td>N/A</td>
<td>N/A</td>
<td>N/A</td>
<td>A</td>
<td></td>
</tr>
</tbody>
</table>

Table 3

Measuring the interoperabilities.

<table>
<thead>
<tr>
<th>( b_{a} )</th>
<th>INF</th>
<th>EF</th>
<th>LF</th>
<th>ISL</th>
</tr>
</thead>
<tbody>
<tr>
<td>INF</td>
<td>0.79</td>
<td>0.4</td>
<td>0.1</td>
<td>0.002</td>
</tr>
<tr>
<td>EF</td>
<td>0.65</td>
<td>0.51</td>
<td>0.25</td>
<td>0.03</td>
</tr>
<tr>
<td>LF</td>
<td>0.41</td>
<td>0.35</td>
<td>0.29</td>
<td>0.06</td>
</tr>
<tr>
<td>ISL</td>
<td>0.28</td>
<td>0.2</td>
<td>0.15</td>
<td>0.1</td>
</tr>
</tbody>
</table>

Here E, C, and A stand for Environment, Consumption and Agents respectively.
6.3. Improving effect of the network

A well designed social network can increase the number of friendships and/or decrease awareness-threshold of agents (i.e. decrease the tendency to stay in their initial behavior). Here we show the behavior of the system when we increase max link generation $\theta_{\text{max}}$. Fig. 15 compares the results of networks with $\theta_{\text{max}} = 1$ and $\theta_{\text{max}} = 3$ (i.e. average link generation equal to 2) when awareness-threshold is equal to 0.1. This figure shows how the social network increases the effects of economical incentives. 1st quarter, median, and third quarter in the network with $\theta_{\text{max}} = 3$ are three time faster than $\theta_{\text{max}} = 1$. Both systems may converge after 400 time periods in some cases, however, 90% of the times the higher link generation converges at least 20% faster. Fig. 15(b) shows how the distribution of convergence shifts to left (i.e. converges faster).

We checked the behavior of the topology of the network by log–log plots [6,71]. Fig. 16 compares the scale-free behavior of the network for $\theta_{\text{max}} = 1$ and $\theta_{\text{max}} = 3$ and depicts the scale-free metric.

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increases from 1.47 to 1.81 when we increased $9_{\text{max}}$. This shows how regulators can improve the convergence time by sharing information between agents or by encouraging them to increase their friendships via social electricity networks.

6.4. Externalities and irrationality

Characteristics of agents (such as irrationality) and the effects of externalities (such as a fashion effect) are not considered in most of the previous studies that modeled electricity consumptions as a complex adaptive system. We analyze the impact of these factors on the social/swarm layer by incorporating them into the agent decisions and study their effect on objectives and control strategies. Considering irrationality helps us to create more realistic cases. We propose discrete choice models (Eq. (19)) based on the total reward $\pi$ and the interoperability classification to study the behavior of irrational agents. We consider two types of irrationality (namely: $\text{Irr-I}$ and $\text{Irr-II}$). The probability that agent $y$ does not switch to the new pattern even if the $p$ value of the new pattern is higher than the $p$ value of the old pattern (i.e. $\text{Irr-I}$) is given by,

$$\text{Prob}_y = \frac{\exp(k_I \pi_{\text{New}})}{\exp(k_I \pi_{\text{New}}) + \exp(k_I \pi_{\text{Old}})}$$  \hspace{1cm} (19)$$

where, $\pi_{\text{New}}$ and $\pi_{\text{Old}}$ are the new and old values for the total reward $p$ and $k_I$ shows the sensitivity of the agents to differences between the $\pi$ values (the higher the $k_I$ the more sensitive). The probability that agent $y$ does not switch to the new pattern even if the $\pi$ values do not satisfy the switching threshold (i.e. $\text{Irr-II}$) can be measured by similar formulation with a new sensitivity factor $k_{II}$.

Fig. 17 compares behaviors of completely rational agents ($\text{Irr} = 0$) with strongly irrational/non-sensitive agents ($k_I = 0.1; k_{II} = 0.1$) and weak irrational/sensitive agents ($k_I = 1; k_{II} = 1$) scenarios. The weak irrational scenario does not converge to any pattern. The strongly irrational scenario converges with an almost similar temporal distribution to rational agents.
However, this simulation of the system does not converge to a pattern of low dis-uniformity but it converges to the pattern that had the highest initial population.

Consumers with the same patterns may create a community in the network. These communities can become dominant and restrict the influence of other patterns even if they have higher \( \pi \) values. Generally we can observe that sometimes the system does not evolve to the situations with lower dis-uniformity. This results from the effect of emergent behavior of consumers in interrelationships with each other in the network.

6.5. Effects of saturated interrelationships

Recent studies show the degree distribution for friendship in growing networks may not be scale-free in the long run \[87\]. The tail decays faster than power-law with increasing size of links and can converge to a Gaussian distribution. Here, when an agent has more than a critical number of links, new edges cannot connect to it. To create this environment (see Section 3.2) we group agents to active or inactive. All new agents are created active. An agent becomes inactive when it reaches a maximum number of links. Inactive agents cannot receive new links. This constraint leads to a single-scale network where the degree of nodes follows a truncated Gaussian distribution.

We study the effect of saturation by comparing Gaussian Distribution (with a maximum number of 4 friends/influencer) to an unbounded scale-free network (power-law distribution) in Fig. 18. This shows regulators should try to avoid Gaussian distribution node degrees by motivating agents to not saturate their friendships. From Fig. 18(b), we note the convergence of entropy occurs faster in most cases in scale-free networks. However, the scale-free network has a longer right tail and in some cases never converges.

6.6. Significant factors

To examine importance and effect of the parameters of the social network on the system outputs, we design two full factorial experiments. We study the system responses by \( \eta_1 \) (the average total rewards of agents), \( D^q \) (the total dis-uniformity of the system), and \( E^q \) (the entropy of the system). An Exponential Weighted Moving Average (EWMA) with discount factor equal to 0.005 is used for weighting the data points at older periods where the number of periods \( q = 1 \) to 400. We study the effect of the social network size by considering two levels (200 and 1000) for the initial population. To study the impact of group vs. individual rewards for minimizing dis-uniformity, we examine two levels for the weight of individual dis-uniformities (\( k_r = k_b \) and \( k_r = 2k_b \)). Also, we vary attributes of pattern \( i \) from a normal utility (Price = 5, Convenience = 4, Glamour = 3) to a weak utility (Price = 8, Convenience = 3, Glamour = 2). The P-values of experimental results for the \( 2^3 \) full factorial experiment with 30 replications are presented in Table 4. The results are created by MiniTab and 0.000 means the P-value is less than 0.05. Note that the normality test for residuals was not convincing. We tried several transformations for responses (e.g. Box-Cox power including square root and Log). A logistic transformation, \( \log([\text{Response} - \text{minResponse}] / (\text{maxResponse} - \text{Response})) \), improved the results of the normality test.
Fig. 19(a), (b), and (c) depict the effect of \( P X_i, K_r, \) and \( U \) on the responses. The results show that the population size is not a significant factor for the defined responses of the system; however, the utility and the weight of individual dis-uniformities should be considered as significant factors. \( K_r \) has the largest significant effect and \( U \) has the second largest significant effect on the total rewards \( \pi^i \). Effect of \( U \) and interaction effect of \( U \) and \( K_r \) on the total dis-uniformity \( D^i \) and entropy \( E^i \) are significant.

In another experiment we study the topology of the network by using the similar responses and leveling the node degree distribution to scale-free and single-scale. Also, we consider two levels for the max link generation (\( \text{max}_\text{link} = 1 \) and \( \text{max}_\text{link} = 6 \)). The p-values of experimental results for the 2\(^2\) full factorial experiment are presented in Table 5.

Fig. 20(a), (b), and (c) depict the effect of topology and max link generation on the responses. The results show that all of them are significant factors. Topology, max link generation, and their interaction have almost a similar size of effect on the total rewards \( \pi^i \) and the total dis-uniformity \( D^i \). Topology has a slightly larger effect in comparison to max link generation. Likewise, max link generation has a smaller effect on entropy in comparison to topology of the network and the interaction effect of max link generation and topology.

### 6.7. Effect of social education

Social education refers to activities by super agents that influence an individual’s behavior to effect a specific pattern. To study effects of social education we consider a super influencer agent (e.g. a utility company or celebrity) which follows a specific pattern (e.g. pattern \( i \)). This super influencer agent is connected to \( h \) percent of other agents randomly and uses the interoperability and interrelationship rules similar to other agents. However, this agent never switches its pattern. Social educations and advertisements can increase the percentage of the agents who get influenced by the super influencer (i.e. larger \( h \)). Fig. 21 compares the convergence time of the system based on \( h \). The figure shows even if only 20% of agents are connected to the super influencer agent, there is a huge improvement in the convergence time. Moreover, it reduces the

---

**Table 4**

<table>
<thead>
<tr>
<th>Response</th>
<th>P reward</th>
<th>P dis-uniformity</th>
<th>P entropy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Population</td>
<td>0.268</td>
<td>0.677</td>
<td>0.174</td>
</tr>
<tr>
<td>( K_r )</td>
<td>0.000</td>
<td>0.447</td>
<td>0.018</td>
</tr>
<tr>
<td>Utility</td>
<td>0.000</td>
<td>0.003</td>
<td>0.000</td>
</tr>
<tr>
<td>Population ( \times ) ( K_r )</td>
<td>0.169</td>
<td>0.205</td>
<td>0.174</td>
</tr>
<tr>
<td>Population ( \times ) Utility</td>
<td>0.534</td>
<td>0.709</td>
<td>0.728</td>
</tr>
<tr>
<td>( K_r ) ( \times ) Utility</td>
<td>0.004</td>
<td>0.004</td>
<td>0.000</td>
</tr>
<tr>
<td>Population ( \times ) ( K_r ) ( \times ) Utility</td>
<td>0.200</td>
<td>0.252</td>
<td>0.096</td>
</tr>
</tbody>
</table>

**Table 5**

<table>
<thead>
<tr>
<th>Response</th>
<th>P reward</th>
<th>P dis-uniformity</th>
<th>P entropy</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Topology</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
<tr>
<td>Link Generation</td>
<td>0.002</td>
<td>0.000</td>
<td>0.121</td>
</tr>
<tr>
<td>Topology ( \times ) Link Generation</td>
<td>0.000</td>
<td>0.000</td>
<td>0.000</td>
</tr>
</tbody>
</table>

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right tail of the distribution of convergence significantly (all agents converge before 350 time periods) i.e. the system is more predictable and has less fluctuation. Note that we run the simulation for 400 time periods and if the agents do not converge before 400 periods their convergence time will be presented in time period = 400. The figure also shows a significant improvement on the distribution of convergence specially its right tail, if we encourage another 20% of agents to connect to super influencer (i.e. \( \eta = 40 \) in comparison to \( \eta = 20 \)). The size of this effect decays for larger \( \eta \).

Another impact of social education or advertisements can improve the interoperability between the agents. Fig. 22 shows how investment on improving the effects of influencer agent on other classes (i.e. the first column in Table 3) changes the convergence time of the system. Here, we assume social investments improve these effects by 5%, 10%, 15%, and 20% for a fixed amount of \( \eta = 20\% \). This figure shows if we only facilitate the interoperability of influencer agents by 5%, the maximum convergence time decrease significantly. This strategy increases the system predictability but does not change the other parameters of the convergence distribution (e.g. min and median). Based on Figs. 21 and 22 managers and decision makers can invest on facilitating the interoperability of utility companies or celebrities on the society instead of trying to connect more agents to the super influencer in the network. However, first we need 20 to 40 percent of agents to get connected to the super influencer.

7. Framework notation and limitations

This study examines how consumption behavior is diffused in a population. Managerial insights about the qualities that make the diffusion successful are offered by this study. Also the importance of social networks and peer to peer conversations are examined here. The S-shape convergence in the pattern of behavior and bell-shape curves of frequency of convergence depict the similarity of the behavior of our ECAS and Bass Diffusion Model [17,68]. A comprehensive discussion on comparison of CASs and diffusion models is presented by Ref. [82]. Table 6 summarizes the notation used throughout the paper.

Previous field experiments and theoretical studies addressed the importance of social interactions in electricity end-used load management (see cited references in Section 1.1 and Section 2), however, the authors of this paper could not find concrete evidence-based studies that examine effects of social networks on the power systems. This study assumes a scale-free social network between electricity users that is the most common characteristic of other social networks. This assumption is relaxed in Section 6.5 to study single-scale behavior of a Gaussian network. Section 6 analyzes the behavior of the social network under variety of different circumstances such as irrationality, saturated friendships, and social education.

In this paper, conceptual inclusion of a social network of heterogeneous consumers with cognitive decision making capabilities (goal directed and adaptive agents) permits our attentions to the possibility of complex adaptive unintended or unforeseen consequences from the viewpoint of electricity market operators. The limitations of this study provide a high-level direction for future researches as follows:

1. Empirical validation of the framework with the real-world electricity markets data could lead to precise specifications,
2. Information technology (cyber-physical) constraints could be incorporated in the social layer interoperabilities,
3. Different bidding and auctions strategies in an electricity market and their effects in the vertical interactions of the social and decision layers could be tested in the framework.

4. DR implementation issues and practical DR initiative concerns in electricity markets (contracts, offers, and other market activities) could be added to the modeling constraints.

5. Architectural and topological constraints of an electricity power grid could be considered in a detailed physical layer and its vertical interactions with the social layer (this paper only examined the horizontal interaction of the social network in Fig. 3). These vertical interactions can be considered by:
   - effects on the social network structure (e.g., two or more islands that are connected with one or few influencers or other classes of interoperability),
   - effects on interoperability or interrelationships (e.g., physical constraints can change the interrelationships in different parts of the network),
   - additional constraints on friendships (e.g., disable relationships or increase the tendency to make a relation in some parts of the network),
   - a social network that has different characteristics (e.g., growth rate and link generations) in different geographical locations because of physical structures.

8. Conclusion

This study takes a mathematical and computational approach to a socio-technical model combining social behavior, economics and technology. The complex engineered system is modeled as consisting of a social layer of agents and a decision layer of external incentives and agent optimization. System behavior emerges and the system evolves dynamically through consumer agent decisions. The modeling and solution methodology address shortcomings in previous approaches and advances our ability to model and understand ECAS behaviors through computational intelligence. The specific model used facilitates reduction of electricity consumption variability referred to as dis-uniformity.

Unlike traditional stochastic learning methods that are based on limited memory of past experiences and utility optimization models that are built by rationality and decision theory, our approach combines both backward and forward looking perspectives. This combination enables us to invest individuals with more concrete cognitive capabilities. This ABM agents are adaptive (can learn based on social education), goal-directed (adjust themselves or their interactions based on a goal), and heterogeneous (their attributes and behaviors may vary and change dynamically). Moreover, complex behaviors such as altruistic versus selfish and cooperation versus competition can be studied by our approach.

Within the electricity context, we develop methods to enable changing consumption patterns of end-users and load aggregators through incentives and social education. We have advanced understanding of the interaction between social behaviors and economical incentives for load management and impacting peak demand. Furthermore, we have provided a toolkit for regulators and managers to help predict behaviors and trajectories of the ECASs based on the status of variables. This enables finding more effective and efficient strategies to change behavior. This framework can be extended to other ECASs.

Finally, we build a baseline to study emergence behavior of electricity consumers. This study shows how the social network topology impacts consumer behavior patterns. Load aggregators...
and system operators can apply this study to examine the value of investments in education and smart technology vs. capacity. We also show how the degree of irrationality in micro level of a system affects the convergence in macro level.

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