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A deep learning and gamification approach to improving human-building interaction and energy efficiency in smart infrastructure

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HIGHLIGHTS

- Discrete Choice Models model occupant actions through machine learning algorithms.
- Deep Learning shows outstanding potential for sequential decision making.
- Artificial Intelligence can generate high dimensional dynamic occupancy usage data.
- Gamification in human-centric cyber-physical systems promotes energy efficiency.
- Participation in social game communicates usage data and facilitates forecasting.

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ABSTRACT

In this paper, we propose a gamification approach as a novel framework for smart building infrastructure with the goal of motivating human occupants to consider personal energy usage and to have positive effects on their environment. Human interaction in the context of cyber-physical systems is a core component and consideration in the implementation of any smart building technology. Research has shown that the adoption of human-centric building services and amenities leads to improvements in the operational efficiency of these cyber-physical systems directed toward controlling building energy usage. We introduce a strategy that incorporates humans-in-the-loop modeling by creating an interface to allow building managers to interact with occupants and potentially incentivize energy efficient behavior. Game theoretic analysis typically relies on the assumption that the utility function of each individual agent is known a priori. Instead, we propose a novel benchmark utility learning framework that employs robust estimations of occupant actions toward energy efficiency. To improve forecasting performance, we extend the benchmark utility learning scheme by leveraging Deep Learning end-to-end training with deep bi-directional Recurrent Neural Networks. We apply the proposed methods to high-dimensional data from a social game experiment designed to encourage energy efficient behavior among smart building occupants. Using data gathered from occupant actions for resources such as room lighting, we forecast patterns of resource usage to demonstrate the performance of the proposed methods on ground truth data. The results of our study show that we can achieve a highly accurate representation of the ground truth for occupant resource usage. For demonstrations of our infrastructure and for downloading de-identified, high-dimensional data sets, please visit our website (*smartNTU* demo web portal: https://smartntu.eecs.berkeley.edu)

1. Introduction

Nearly half of all energy consumed in the U.S. can be attributed to usage by residential and commercial buildings [1]. In efforts to improve energy efficiency in buildings, researchers and industry leaders have attempted to implement novel control and automation approaches alongside techniques like incentive design and adaptive price adjustment to more effectively regulate energy usage. Another common avenue for the regulation of energy usage in buildings is through their on-site building and facility managers. Building managers are obligated to maintain an energy efficient schedule according to a standard operating procedure. Even with these considerations, there is still a tremendous need for scalable and robust frameworks that can efficiently coordinate and control building resource usage in the presence of

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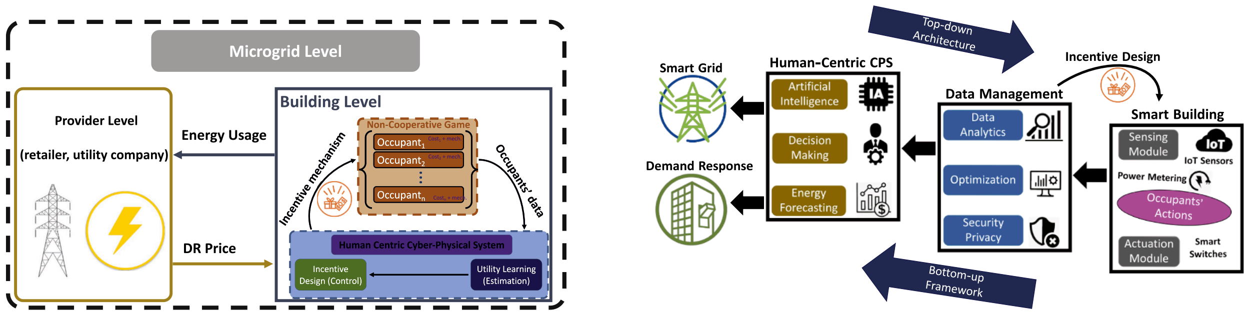


((a)) Gamification abstraction for *Human-Centric Cyber-Physical Systems*

((b)) Overview of the proposed block diagram—research design framework

Fig. 1. Block diagram & gamification abstraction of the proposed human-building interaction approach.

confounding dynamics such as human behavior. To summarize the space of solutions, an ideal smart building infrastructure accommodates a variety of occupant preferences including thermal comfort [2], satisfaction/well-being [3], lighting comfort [4], acoustical quality [5], indoor air quality [6], indoor environmental monitoring [7], privacy [8] and productivity [9], while simultaneously optimizing for energy efficiency and agile connectivity to the grid.

Recently, utility companies have invested in demand response programs that can address improper load forecasting while also helping building managers encourage energy efficiency among building occupants [10,11]. Commonly, the implementation of these programs is enacted on a contract basis between utility providers and the consumers under arranged conditions of demand/usage. The building managers will then be bound by contract to operate according to the agreed-upon schedule. However, the conditions of these contracts are static and do not consider dynamic changes in occupant behavior or preferences, which can result in discrepancies in demand/usage expectations. To facilitate the adoption of more dynamic protocols for demand response, our setup features a gamification interface (seen in the building level in Fig. 1(a)) that allows building managers to interact with a building's occupants. By leveraging our gamification interface, retailers and utility companies at the provider level can utilize a wealth of dynamic and temporal data on building energy usage—extending even to occupant usage predictions—in order to customize demand response program approaches to observed or predicted conditions [12,13]. Above all, our gamification interface is designed to support engagement and integration on multiple levels in a *human-centric cyber-physical system*. Human-centric cyber-physical systems can be defined as follows:

Systems or mechanisms that combine computer-based technologies with physical processes to integrate direct human coordination through various interaction modalities.

The availability of these resources allows researchers to demonstrate gaming data in a discrete choice setting, run simulations that include data on dynamic occupant preferences, test correlations between actions and external parameters (e.g. provided weather metrics), and leverage temporal data sets in demand response program scenarios [12,13].

The cooperation of human agents with building automation in smart infrastructure settings helps improve system robustness and sustainability by taking advantage of both the control potential for computational methods and the flexibility provided by humans-in-the-loop elements. The inherent adaptability and simultaneous automation in such a system makes it possible to accommodate a wide variety of dynamic situations that might arise in the maintenance of building infrastructure, like the automatic shifting of demand during peak energy/usage hours. Put into more broad terms, the goal of many infrastructure systems is to enact system-level efficiency improvements by using a high-level *planner* (e.g. facility manager) to coordinate autonomously acting agents in the system (e.g. selfish human decision-makers). It is this type of functionality that makes smart building technology so essential to the development of an ideal *smart city*.

Our approach to efficient building energy management focuses on residential dorm buildings and utilizes cutting-edge Internet of Things (IoT) sensors and cyber-physical system sensing/actuation platforms integrated with the aforementioned gamification interface (Fig. 1(a)). The interface is designed to support occupant engagement and integration while learning occupant preferences over shared resources. It also gives us the ability to try to understand how preferences change as a function of critical factors such as manual control of devices, time of day, and provided incentives. Our gamification framework can be used in the design of incentive mechanisms in the form of fair compensation that help to realign agent preferences with those of the planner, which are often representative of system-level performance criteria.

We present a social game aimed at incentivizing occupants to modify their behavior so that the overall energy consumption in their room is reduced. In certain living situations, occupants in residential buildings are not responsible for paying for the energy resources they consume. For this reason, there is often an imbalance between the motivations of the facility manager and those of the occupants. The competitive aspects of the social game framework motivate occupants to address their inefficiencies while encouraging responsible energy usage on an individual basis.

At the core of our approach is the decision to model the occupants as non-cooperative agents who play according to a sequential discrete choice game. Discrete choice models have been used extensively to investigate representations for scenarios like variation in modes of transportation [14], demand for organic foods [15], and even school social interactions [16]. Our framework is centered around learning agent preferences over room resources, such as lighting, as well as external parameters like weather conditions, high-level grid control, and provided incentives. Specifically, agents are strategic entities that make decisions based on their own preferences without consideration of other decision makers. The game-theoretic framework allows for qualitative insights to be made about the outcome of this selfish behavior—more so than a simple prescriptive model—and, more importantly, can be leveraged in designing incentive mechanisms for the purposes of motivating agents.

The broader motivation of this paper is to introduce a general framework that utilizes game theoretic concepts to learn models of players' decision-making in residential buildings, which is made possible by the implementation of our social game setting. We present a variety of benchmark utility learning models and a novel pipeline for the efficient training of these models. In order to boost predictive power, we propose end-to-end Deep Learning models focused on the utilization of deep recurrent neural networks for analyzing gaming data. To handle sequential information dependencies in our data, we implement our Deep Learning architecture using Long Short Term Memory cells (LSTM). Lastly, we provide a demo web portal for demonstrating our infrastructure and for downloading de-identified, high-dimensional data sets.[1] High-dimensional data sets can serve either as a benchmark for alternative discrete choice model learning schemes or as a great source for analyzing occupant energy usage in residential buildings.

The body of the paper is organized as follows. Previous works are surveyed in Section 2 with an emphasis on human-centric models with integration in smart grid infrastructures. Section 3 describes the social game experiment on the Nanyang Technological University campus and the human decision-making model. Section 4 introduces utility estimation along with several proposed machine learning & novel Deep Learning architectures and algorithms for sequential decision games. Presentation of our results is given in Section 5. We make concluding remarks in Section 6.

2. Related work

Smart grid technology is focused on enabling efficient grid integration and comprehensive analysis to support advances in renewable energy sources, power systems management, minimization of inefficiencies in usage, and maximization of user savings. However, challenges in power grid applications, such as the lack of predictability, and the stochastic environment in which the power grid operates complicate the synthesis of an all-encompassing solution. To address these problems, industry and researchers in the fields of power grid design and control have put forth considerable research and development efforts in smart grid design, demand-side management, and power system reliability.

With the help of digital hardware and information technology, smart grid design relies more and more on the development of decision-capable intelligence in the context of grid automation. Novel methods [17] for smart grid design incorporate real-time analysis and stochastic optimization to provide power grid observability, controllability, security, and an overall reduction of operational costs. Specifically, the integration of data analytics and innovative software platforms have led to effective trends in demand-side management [18] and demand response [19]. These studies explored and drew upon methods from behavioral decision research to analyze the decision patterns of users and consumers. The simulations and empirical results from these studies reinforce the significance of forecasting energy demands and the potential advantages of managing these demands by leveraging models of intelligent decision-makers. In this context, we can see that the process of modeling and predicting the actions of decision-makers in the control of large networks is a significant development toward improving the operational efficiency of smart grids.

Game theory can serve as an extremely useful tool for the real-time forecasting of decision-makers in an interactive setting. Classical models from game theory allow for qualitative insights about the outcome of scenarios involving the selfish behavior of competitive agents and can be leveraged in the design of incentives for influencing the goals of these agents. Contemporary research in the energy and power systems domain leverages game theoretic models in a multitude of applications. As previously mentioned, these types of approaches have been implemented in the modeling of various aspects of smart grid control. Specifically, we can observe instances of game theory applications in the context of smart grid demand response programs using methods such as supply-balancing [20], hierarchical Stackelberg game settings [21], and Vickrey-Clarke-Groves (VCG) auction mechanisms [22].

The use of game theoretic models creates new avenues for modeling dynamic economic interactions between utility providers and consumers inside a distributed electricity market [23]. Another example study is the investigation of crowdfunding as an incentive design methodology for the construction of electric vehicle charging piles [24]. Game theory has also been directed toward the optimal design of curtailment schemes that control the fair allocation of curtailment among distributed generators [25]. Expanding on previous work, researchers have studied game theory applications in the context of incentive-based demand response programs for customer energy reduction as well [26]. In these types of applications, customer interaction with the incentive provider is modeled using game theory while their engagement is represented probabilistically.

In the majority of the previously discussed game theoretic modeling applications, results are generated purely by simulation without the use of real data. Furthermore, previous applications neglect to propose any novel techniques for learning the underlying utility functions that dynamically predict strategic actions. Due to these limitations, we cannot reasonably expect to learn (or estimate) user functions in a gaming setting nor generalize results to broader scenarios. In real-life applications, the game theoretic models are not known a priori; therefore, the developed methods should have some way to account for data-driven learning techniques. In our past work, we have explored utility learning and incentive design as a coupled problem both in theory [27–29] and in practice [30–32] under a Nash equilibrium model. Our utility learning approaches are presented in a platform-based design flow for smart buildings [33]. The broader purpose of this paper is to present a general learning framework that leverages game theoretic concepts for learning models of occupant decision making in a competitive setting and under a discrete set of actions.

In Fig. 1(b), we present a block diagram of our proposed research design framework toward building energy management from both a top-down and bottom-up perspective, motivated by previous model illustrations [33]. The block diagram consists of three layers: the smart building layer, the data management layer, and the top human-centric cyber-physical systems layer. Each layer has some connection between its respective components and upper level abstractions. From the proposed bottom-up framework, the aggregated occupant patterns are processed and passed to an artificial intelligence layer that is capable of real-time energy forecasting, which can then be integrated with applications like demand response programs. Through optimization and data analysis, the proposed design framework leverages advanced incentive design schemes aimed at engaging smart building occupants. In addition, the data management layer provides the opportunity to implement security and privacy protocols against malicious attacks [29].

Contemporary building energy management techniques employ a variety of algorithms in order to improve performance and sustainability. Many of these approaches leverage ideas from topics such as optimization theory and machine learning. Our goal was to improve building energy efficiency by introducing a gamification system that engages users in the process of energy management and integrates seamlessly through the use of a human-centric cyber-physical framework. There exists a considerable amount of previous work demonstrating the success of control and automation in the improvement of building energy efficiency [34,35]. Some other notable techniques implement concepts such as incentive design and adaptive pricing [36,37]. Modern control theory has been a critical source of inspiration for several approaches that employ ideas like model predictive and distributed control and have demonstrated encouraging results in applications like HVAC. Unfortunately, these control approaches lack the ability to consider the individual preferences of occupants, which highlights a significant advantage of human-centric scenarios over contemporary methods. While machine learning approaches are capable of generating optimal control designs, they fail to adjust to occupant preferences and the associated implications of these preferences to the control of building systems. The heterogeneity of user preferences in regard to building utilities is considerable and necessitates a system that can adequately account for differences from occupant to occupant.

Clearly, the presence of occupants greatly complicates the determination of an efficient building management system. With this in mind, focus has shifted toward modeling occupant behavior within the system in an effort to incorporate their preferences. To accomplish this

[1] *smartNTU* demo web portal: https://smartntu.eecs.berkeley.edu.

task, the building and its occupants are represented as a multi-agent system targeting occupant comfort [34]. First, occupants and managers are allowed to express their building preferences, and these preferences are used to generate an initial control policy. An iteration on this control policy is created by using a rule engine that attempts to find compromises between preferences. Some drawbacks of this control design are immediately apparent. There should be some form of communication to the manager about occupant preferences. In addition, there is no incentive for submission of true user preferences and no system for considering occupant feedback. Other related topics in the same vein focus on grid integration [38], while still others consider approaches for policy recommendations and dynamic pricing systems [36].

As alluded to previously, the key to our approach is the implementation of a social game among users in a non-cooperative setting. Similar methods that employ *social games* have been applied to transportation systems with the goal of improving flow [39,40]. Entrepreneurial ventures have also sought to implement solutions of their own to the problem of managing building energy efficiency.[2],[3],[4],[5] Finally, it has been shown that societal network games are useful in a *smart city* context for improving energy efficiency and human awareness [41].

The critical motivation behind the social game context is to create friendly competition between occupants. In turn, this competition will encourage occupants to individually consider their own energy usage and, hopefully, seek to improve it. This same gamification technique has also been used as a way to educate the public about energy usage [42,43]. Additionally, it has been cleverly implemented in a system that presents feedback about overall energy consumption to occupants [44]. Another notable case of a gamification methodology was used to engage individuals in demand response (DR) schemes [45]. In this application, each of the users is represented as a utility maximizer within the model of a Nash equilibrium where occupants gain incentive for reduction in consumption during DR events. In contrast to approaches that target user devices with known usage patterns [45], our approach focuses on personal room utilities, such as lighting, without initial usage information, which simulates scenarios of complete ignorance to occupant behaviors. For our method, we utilize past user observations to learn the utility functions of individual occupants by way of several novel algorithms. Using this approach, we can generate excellent prediction of expected occupant actions. Our unique social game methodology simultaneously learns occupant preferences while also opening avenues for feedback. This feedback is generated through individual surveys that provide opportunities to influence occupant behavior with adaptive incentive. With this technique, we are capable of accommodating occupant behavior in the automation of building energy usage by learning occupant preferences and applying a variety of novel algorithms. Furthermore, the learned preferences can be adjusted through incentive mechanisms to enact improved energy usage.

A series of experimental trials were conducted to generate real-world data, which was then used as the main source of data for our approach. This differentiates our work from a large portion of other works in the same field that use simulations in lieu of experimental methods. In many cases, participants exhibit a tendency to revert to previously inefficient behavior after the conclusion of a program. Our approach combats this effect by implementing incentive design that can adapt to the behavior and preferences of occupants progressively, which ensures that participants are continuously engaged. From a managerial perspective, the goal is to minimize energy consumption while maximizing occupant comfort. With this social game framework, the manager is capable of considering the individual preferences of the occupants within the scope of the building's energy consumption. This social game system could potentially offer an unprecedented amount of control for managers without sacrificing occupant comfort and independence.

3. Smart building social game: implementation & human decision-making

In this section, we introduce our social game concept as a gamification application implemented at Nanyang Technological University (NTU) residential housing apartments, along with the software architecture design for the deployed Internet of Things (IoT) sensors. In addition to the implementation of this gamification application, we abstract the agent decision-making processes in a game theoretic framework and introduce the discrete choice theory that we draw upon for forecasting agent actions with high accuracy.

3.1. Description of the social game experiment

Our experimental environment is comprised of residential housing single room apartments on the Nanyang Technological University campus. We designed a social game web portal such that all single room dorm occupants could freely view their daily room's resource usage with a convenient interface. In each dorm room, we installed two Internet of Things (IoT) sensors[6]—one close to the desk light and another near the ceiling fan. With the deployment of IoT sensors, dorm occupants can monitor in real-time their room's lighting system (desk and ceiling light usage) and HVAC (ceiling fan and A/C usage) with a refresh interval of up to one second.

Dorm occupants are rewarded with points based on how energy efficient their daily usage is in comparison to their past usage before the social game was deployed. The past usage data that serves as our baseline is gathered by monitoring occupant energy usage for approximately one month before the introduction of the game for each semester. Using this prior data, we calculated a weekday and weekend baseline for each of an occupant's resources. We accumulate data separately for weekdays and weekends so as to maintain fairness for occupants who have alternative schedules of occupancy (e.g. those who tend to stay at their dorm room over the weekends versus weekdays). We employ a lottery mechanism consisting of several gift cards awarded on a bi-weekly basis to incentivize occupants; occupants with more points are more likely to win the lottery. Earned points for each resource is given by the following equation:

$$\hat{p}_i^d(b_i, u_i) = s_i \frac{b_i - u_i^d}{b_i} \tag{1}$$

where $\hat{p}_i^d$ is the points earned at day d for room's resource i which corresponds to ceiling light, desk light, ceiling fan, and A/C. Also, b_i is the baseline calculated for each resource i, u_i^d is the usage of the resource at day d, and s_i is a points booster for inflating the points as a process of framing [46]. This process of framing can greatly impact a user's participation, and it is routinely used in rewards programs for credit cards among many other point-based programs used in industry. In addition, we rewarded dorm occupants for the percentage of savings (1) because we felt it was important to motivate all of the participants to optimize their usage independent of the total amount of energy consumed in their normal schedule. However, over-consumption resulted in negative points.

In Fig. 2(a), we present how our graphical user interface was capable of reporting to occupants the real-time status (on/off) of their devices, their accumulated daily usage, time left for achieving daily

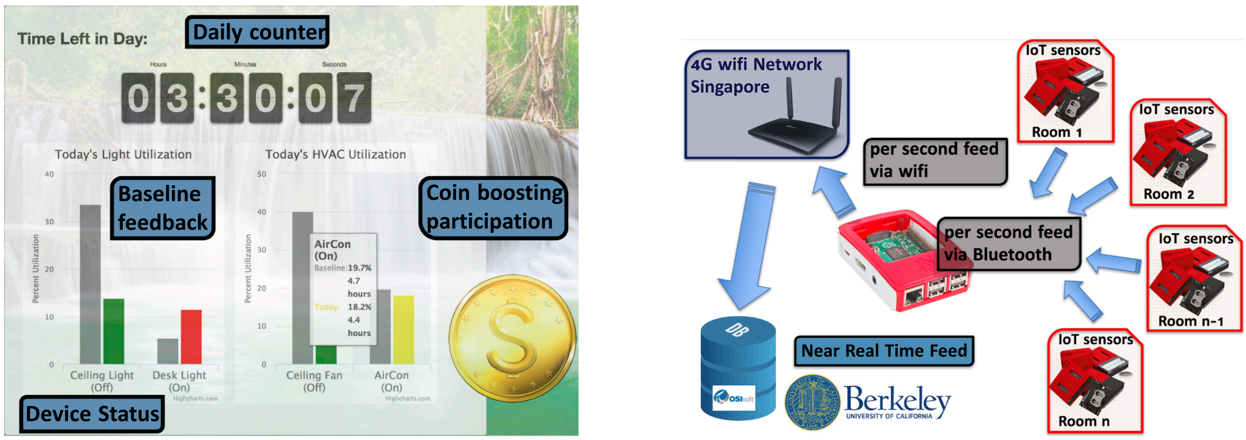
[2] https://comfyapp.com.

[3] https://coolchoices.com/how-it-works/improve.

[4] https://opower.com.

[5] https://www.keewi-Inc.com/index.php.

[6] *IoT sensor tag*: http://www.ti.com/ww/en/wirelessconnectivity/sensortag/index.html.



((a)) Graphical user interface (GUI)

((b)) Social game dataflow architecture design

Fig. 2. Graphical user interface (GUI) and dataflow design for social game.

baseline, and the percentage of allowed baseline being used by hovering above their utilization bars. In order to boost participation, we introduced a randomly appearing coin close to the utilization bars with the purpose of incentivizing occupants to log into the web portal and view their usage. The coin was designed to motivate occupants towards viewing their resource usage and understanding their impact to energy consumption by getting exact usage feedback in real-time. Based on this game principle, we gave occupants points when they clicked on the coin, which could increase both their perceived and actual chances of winning the rewards.

The residential housing single room apartments on the Nanyang Technological University campus are divided into four blocks, each of which having two floors. In this space, there is a total of seventy-two occupants who are eligible to participate in the social game. Participation in our social game platform was voluntary. In the Fall 2017 version, we included ceiling light, desk light, and ceiling fan resources in the graphical user interface for the social game, while in the Spring 2018 version we included all of the potential resources that were available.

3.2. Internet of Things (IoT) system architecture

We enabled the design and implementation of a large-scale networked social game through the utilization of cutting-edge Internet of Things (IoT) sensors. In total, we have deployed one hundred and forty-four sensors in single room dorms. These are part of a hardware and software infrastructure that achieves near real-time monitoring of various metrics of resource usage in each room, like lighting and A/C. Moreover, our system is capable of saving occupant actions in the web portal. Weather data is gathered from an externally-installed local weather monitoring station at per second resolution. The actual design and dataflow is depicted in Fig. 2(b).

Utilizing the data gathered from each dorm room, we leveraged several indoor metrics like indoor illuminance, humidity, temperature, and vibrations for the ceiling fan sensor. Having performed various tests during Summer 2017 within the actual unoccupied dorm rooms, we have derived simple thresholds indicating if a resource is in use or not. For instance, the standard deviation of acceleration gathered from the ceiling fan mounted sensor is an easy way to determine whether the ceiling fan is in the on state. Additionally, by combining humidity and temperature values, we were able to reliably identify whether A/C is in use with limited false positives. Our calibrated detection thresholds are robust over daylight patterns, external humidity/temperature patterns, and measurement noise introduced by IoT sensors.

While we receive data from various dorm room sensors, our back-end processes update the status of the devices in near real-time in each occupant's account and update points based on their usage and point formula (1). This functionality allows occupants to receive feedback, view their points balance, check rankings, and more. In order to allow participants to assess and visualize their energy efficient behavior, each user's background in the web portal changes based on their ranking and energy efficiency. We used background pictures of rain forest settings for encouraging the more energy efficient occupants and images of desert scenes to motivate those with limited energy savings. For a live view of our web portal,[7] you can visit our demo web-site, which serves as a demonstration of the game and as a hub for downloading de-identified per-minute aggregated data.

3.3. Social game data set

As a final step, we aggregate occupant data in per-minute resolution. We have several per-minute features like time stamp, resource status, accumulated resource usage in minutes per day, resource baseline, gathered points (both from game and surveys), occupant ranking over time, and number of occupant visits to the web portal. In addition to these features, we add several external weather metrics like humidity, temperature, and solar radiation.

After gathering a high-dimensional data set with all of the available features, we propose a pooling & picking scheme to enlarge the feature space and then apply a Minimum Redundancy and Maximum Relevance (mRMR) [47] feature selection procedure to identify useful features for our predictive algorithms. We pool additional features from a subset of the already derived features by leveraging domain knowledge. Specifically, we consider two different feature types: dummy features (using one-hot encoding) and resource features. Dummy features represent intangible variables relating to weekly or seasonal events such as weekends in the former case and holidays in the latter. Resource features include deterministic data sets gathered by our instrumentation such as daily percentage of resource usage.

3.4. Agent decision-making model

Discrete choice theory is greatly celebrated in the literature as a means of data-driven analysis of human decision-making. Under a discrete choice model, the possible outcome of an agent can be predicted from a given choice set using a variety of available features describing either external parameters or characteristics of the agent. We use a discrete choice model as a core abstraction for describing occupant actions related to their dorm room resources.

[7] *smartNTU* demo web portal: https://smartntu.eecs.berkeley.edu.

Consider an agent i and the decision-making choice set which is mutually exclusive and exhaustive. The decision-making choice set is indexed by the set $\mathcal{I} = \{\mathcal{J}^1, ..., \mathcal{J}^S\}$. Decision maker i chooses between S alternative choices and would earn a **representative utility** f_i for $i \in \mathcal{I}$. Each decision among decision-making choice set leads agents to get the highest possible utility, $f_i > f_j$ for all $i, j \in \mathcal{I}$. In our setting, an agent has a utility which depends on a number of features x_z for $z = 1, ..., N$. However, there are several unobserved features of the representative utility which should be treated as random variables. Hence, we define a **random utility** decision-making model for each agent given by

$$\hat{f}_i(x) = g_i(\beta_i, x) + \epsilon_i \tag{2}$$

where ϵ_i is the unobserved random component of the agent's utility, $g_i(\beta_i, x)$ is a nonlinear generalization of agent i's utility function, and where

$$x = (x_1, ..., x_{i-1}, x_{i+1}, ..., x_N) \in \mathbb{R}^N \tag{3}$$

is the collective n features explaining an agent's decision process. The choice of nonlinear mapping g_i and x abstracts the agent's decision; it could represent, e.g., how much of a particular resource they choose to use and when an agent optimizes its usage over a specific resource. Discrete choice models in their classical representation [48] are given by a linear mapping $g_i(\beta_i, x) = \beta_i^T x$ in which ϵ_i is an independently and identically distributed random value modeled using a Gumbel distribution.

3.5. Game formulation

To model the outcome of the strategic interactions of agents in the deployed social game, we use a *sequential non-cooperative discrete game* concept. To introduce our generalized decision-making model for each agent (2), a sequential non-cooperative discrete game is given by.

Definition 1. Each agent i has a set $\mathcal{F}_i = f_i^1, ..., f_i^N$ of N **random utilities**. Each random utility j has a convex decision-making choice set $\mathcal{I}_j = \{\mathcal{J}_j^1, ..., \mathcal{J}_j^S\}$. Given a collective of n features (3) comprising the decision process and the temporal parameter T, agent i faces the following optimization problem for their **aggregated random utilities**:

$$\max\{\sum_{i=1}^{N} f_i^T(x) | \, |f_i \in \mathcal{F}_i\}. \tag{4}$$

In the sequential equilibrium concept, we simulate the game defined by the estimated random utility functions per resource to demonstrate the actual decision-making process of each individual dorm occupant. Agents in the game independently co-optimize their aggregated random utilities (4) given a collective of n features (3) at each time instance T. A general incentive design mechanism (1) (seen in the building level of the gamification framework in Fig. 1(a)) motivates their potential actions across various given decision-making choice sets. The above definition extends the definition of a discrete choice model [48] to sequential games in which agents co-optimize several discrete, usually mutually exclusive, choices.

4. Description of benchmark & deep learning methodology

In this section, we explore the utility learning problem using Deep Learning methods that serve to improve forecasting accuracy. From a broader perspective, our goal is to demonstrate how the proposed learning scheme fits into the overall gamification abstraction in Fig. 1. We will show that our utility learning methods lead to accurate energy usage forecasts, which in turn can be integrated in demand response programs (seen in the provider/retailer level in Fig. 1(a)). This goal motivates why we are interested in learning more than a simple predictive model for agents, but rather an exceptional utility-based forecasting framework that accounts for individual preferences, dynamic changes in agent behavior, and heterogeneous actions.

4.1. Benchmark learning framework

In Section 3.4, we introduced an extension to discrete choice models for sequential decision-making over a set of different choices. More concretely, we examine the utility learning problem using a novel pipeline including a variety of statistical learning methods and models that improve estimation and prediction accuracy for our proposed sequential discrete choice model. Furthermore, well-trained classification models serve as an excellent benchmark for our proposed Deep Learning models.

4.1.1. Random utility estimation pipeline

We start by describing the basic components of our proposed random utility estimation pipeline using observed pooled features and data gathered from the game played between agents. Our proposed game (4) is a super set containing classical discrete choice models. Let us now introduce the pipeline formulation as it serves as the basis for the random utility estimation method.

After gathering streaming data in our MySQL data-base (as described in Section 3), we pool several candidate features and expand our feature space. Next, a large set of proposed high-dimensional candidate features is constructed. Using this feature set, we adopt a greedy feature selection algorithm called Minimum Redundancy Maximum Relevance (mRMR) [47]. The mRMR greedy heuristic algorithm utilizes mutual information as the metric of goodness for a candidate feature set. Given the large number of pooled candidate features, mRMR feature selection is a useful method of finding a subset of features that are relevant for the prediction of occupants' resource usage. The mRMR feature selection algorithm is applied to batched gathered data from the first game period either in the Fall or Spring version of the Social Game. From the total number of available feature candidates, we decided to keep nearly half of them.

After getting a number of top performing features as a result of the mRMR greedy algorithm, we apply a simple data pre-processing step with mean subtraction across each individual feature. Mean subtraction centers the cloud of data around the origin along every dimension. On top of mean subtraction, we normalize the data dimensions by dividing each dimension by its standard deviation in order to achieve nearly identical scale in the data dimensions. However, the training phase of the random utility estimation pipeline has one potentially significant challenge, which is the fact that data in almost every resource is heavily imbalanced (e.g. the number of resources with off samples is on the order of 10–20 times more than those with on samples). This is expected considering occupants' daily patterns of resource usage in buildings, but it poses a risk of having potentially poorly trained random utility estimation models.

For optimizing around highly imbalanced data sets, we adapt the Synthetic Minority Over-Sampling (SMOTE) [49] technique for providing balanced data sets for each resource and for boosting prediction (e.g. classification) accuracy. SMOTE over-samples a data set used in a classification problem by considering k nearest neighbors of the minority class given one current data point of this class. The SMOTE algorithm can be initialized by leveraging a pre-processing phase with Support Vector Machines as a grouping step.

After the SMOTE step, we train several classifiers (2) as a final step for the random utility estimation pipeline. Moreover, we propose a base model of logistic regression. In an effort to improve this discrete choice model, we include penalized logistic regression (regLR) with $l1$ norm protocol (Lasso) for the model training optimization procedure, among other classical classification machine learning algorithms. We perform a randomized grid search for optimizing classifiers using the Area Under the Curve (AUC) metric [50], aiming to co-optimize TPR (sensitivity) and FPR (1-specificity).

We use the Area Under the Receiver Operating Characteristic (ROC) Curve as our performance metric. ROC curves describe the predictive behavior of a binary classifier by plotting the probability of true positive rate (i.e. correct classification of samples as positive) over false positive rate (i.e. the probability of falsely classifying samples as positive). For training the proposed machine learning algorithms, we used k-fold cross validation combined with the AUC metric to randomly split the data into training and validation sets in order to quantify the performance of each proposed machine learning model in the training phase. Each machine learning algorithm used in our benchmark pipeline and their respective hyper-parameters are described in more depth in the archived version of this paper [51].

4.2. Leveraging deep learning for sequential decision-making

Let us now formulate a novel Deep Learning framework for random utility estimation that allows us to drastically reduce our forecasting error by increasing model capacity and by structuring intelligent deep sequential classifiers. The architecture for deep networks is adaptive to proposed sequential non-cooperative discrete game models and achieves a tremendous increase to forecasting accuracy. Hence, deep networks achieve an end-to-end training for modeling agents' random utility (2) with extraordinary accuracy. Due to ease of access to big data and the rapid development of adaptive artificial intelligence techniques, energy optimization and the implementation of smart cities has become a popular research trend in the energy domain. Researchers have deployed Deep Learning and Reinforcement Learning techniques in the field of energy prediction [52,53] and intelligent building construction [54].

In our framework of random utility learning in a non-cooperative game setting, deep networks work as powerful models that can generalize our core model (2) by increasing capacity and by working towards an intelligent machine learning model for predicting agent behavior.

4.2.1. Deep neural networks for decision-making

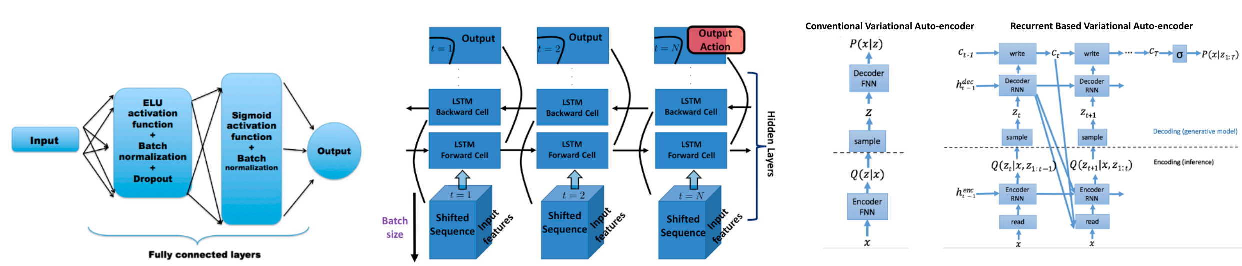
Deep neural network techniques have drawn ever-increasing research interests ever since Deep Learning in the context of rapid learning algorithms was proposed in 2006 [55]. Our approach has the inherent capacity to overcome deficiencies of the classical methods that are dependent on the limited series of features located in the training data set (e.g. such as the features resulting from mRMR in our setting). A deep neural network can be seen as a typical feed-forward network in which the input flows from the input layer to the output layer through a number of hidden layers (in general there are more than two). An illustration of the deep neural network for random utility learning is depicted in Fig. 3(a).

Our proposed deep neural network model for random utility learning includes exponential linear units (ELUs) [56] at each hidden layer. The usage of exponential linear units [56] normally adds an additional hyper-parameter in the search space as a trade-off for significant increases in fitting accuracy due to enormous decrements of "dead" units — a classical problem of rectified linear unit (ReLU) implementations [57]. The output layer is modeled using sigmoid units for classifying agents' discrete choices. The proposed model is optimized by minimizing the cross-entropy cost function using stochastic gradient descent combined with a Nesterov optimization scheme. The initialization of the weights utilizes He normalization [58], which gives increased performance and better training results. Unlike a random initialization, He initialization avoids local minimum points and makes convergence significantly faster. Batch Normalization [59] has also been adapted in our deep neural network framework to improve the training efficiency and to address the vanishing/exploding gradient problems in the training of deep neural networks. By using Batch Normalization, we avoid drastic changes in the distribution of each layer's inputs during training while the deep network's parameters of the previous layers keep changing. Knowing that adding more capacity in our deep neural network model will potentially lead to over-fitting, we apply dropout technique [60] as a regularization step. The dropout technique involves the following procedure in the training phase (both in forward and backward graph learning traversal steps): each neuron, excluding the output neurons, has a probability to be totally ignored. The probability to ignore a neuron is another hyper-parameter of the algorithm and normally gets values between 50% and 70%.

4.2.2. Deep bi-directional recurrent neural networks for sequential decision-making

One of the basic drawbacks of both benchmark random utility learning models as well as the proposed deep neural networks is that they have strong assumptions for the data generation process. An important challenge for efficient learning of sequential decision-making models is the actual modeling of the dependence of future actions of an agent with the present and previous actions. In particular, an agent naturally tries to co-optimize around a set of discrete choices and gains the higher utility (4). Both benchmark models and deep neural networks adopt the assumption of independent and identically distributed data points. One way to model the underlying time series dependencies is through efficient feature engineering and by potentially using a novel feature selection algorithm. In Section 3.3, we use domain knowledge along with a pooling & picking method to create a feature set that can accurately predict agents' behavior. However, this step helps sparingly in the presence of time series dependencies and cannot generalize.

Leveraging the latest Deep Learning models, like recurrent neural networks, we try mainly to address the issue of time dependence by looking at temporal dependencies within the data. Recurrent neural networks have the capability to allow information to persist, even over long periods, by simply inserting loops that point to them. Lately, recurrent neural networks have been implemented with huge success in energy and automotive sectors. Specifically, recurrent neural networks can be applied to energy related fields such as wind energy conversion systems [61,62] and solar radiation prediction [63,64]. In the automotive sector, recurrent neural networks are used for anticipating driver activity [65] in addition to autonomous driving testing [66].



((a)) Architecture of proposed deep neural network ((b)) Architecture of deep bi-directional recurrent neural networks ((c)) Conventional and recurrent based deep auto-encoder

Fig. 3. Proposed deep neural networks, deep bi-directional recurrent neural network, and deep auto-encoders.

Also, vision based autonomous driving systems have been developed using deep convolutional neural networks [67,68].

As we see in the architecture of a deep bi-directional recurrent neural network in Fig. 3(b), information passes from one time step of the network to the next. The information of the network passes to successor nodes. In the case of a bi-directional recurrent neural network, information flows also in the opposite direction to the predecessor. In a simple implementation, however, recurrent neural networks tend to either vanish or become incapable of modeling long-term dependencies. In our proposed novel sequential utility learning model, we enable an end-to-end training using Long Short Term Memory cells (LSTM). Mainly, LSTM includes several gates that decide how long-term—short-term relations should be modeled. The overall output of the LSTM cell is a combination of sub-gates describing the term dependencies [56].

Our deep bi-directional architecture is described in Fig. 3(b). Given an agent's actions, we define a time step N (sliding window of actions), which is a hyper-parameter and models time series dependencies in agent actions. Each training instance in the network is a tensor with the following dimensions: mini-batch size (using a multiple of time step N), target sequence, and all given features.

Our deep network is designed to leverage sequential data and build several layers and time steps of hidden memory cells (LSTMs). Moreover, we propagate the unrolled deep network both forward and backward (bi-directional recurrent neural network) for modeling the exact series time-lagged features for agents' actions. For the proposed deep bi-directional recurrent neural network, we use three hidden layers. To perform classification for the agent actions, we add a fully connected layer containing two neurons (one per class). The fully connected layer is in turn connected to the output of the ending time-step propagating network, and this is finally followed by a soft-max layer, which is what actually performs the classification task. Similar to the deep neural network model, we optimize by minimizing the cross-entropy cost function using stochastic gradient descent combined with a Nesterov optimization scheme. Additionally, we employ an exponentially decaying learning rate as our learning rate schedule. Again, the initialization of the weights utilizes He normalization [58], which gives increased performance and better training results. For dealing with the enormous capacity of the proposed deep network, we apply dropout as the core regularization step.

4.2.3. Deep learning for generative sequential decision models

On top of the existing data set resulting from our experiment, researchers can create other even larger data sets based on the existing ones. The idea of bootstrapping [69] is widely applied both in statistics and machine learning in many applications to help with the creation of new data sets that mimic an original. However, bootstrapping is not a scalable solution. As data sets become larger and larger, the computational complexity restricts the capabilities of the system. In our approach, we propose the use of deep variational auto-encoders [70] as an approach to create a nonlinear manifold (encoder) that can be used as a generative model. Variational auto-encoders formalize the necessary generative model in the framework of probabilistic graphical models by maximizing a lower bound on the log-likelihood of the given high-dimensional data. Furthermore, variational auto-encoders can fit large high-dimensional data sets (like our social game application) and train a deep model to generate data resembling the original data set. In a sense, generative models automate the natural features of a data set and then provide a scalable way to reproduce known data. This capability can be employed either in the utility learning framework for boosting estimation or as a general way to create simulations mimicking occupant behavior/preferences in software like EnergyPlus.[8]

Using such a Deep Learning model, we can acquire generated samples by simply enabling the latent space of the auto-encoder and re-sampling using the decoder component. In Fig. 3(c), we provide the overall idea behind training a variational auto-encoder. We use two hidden layers in encoder and decoder while tying parameters between them. Also, the latent space is modeled using a Gaussian distribution. By using this architecture of deep auto-encoder, however, we limit the generative model in applications in which the data process has a natural time-series dependence. Hence, we proposed the implementation of a recurrent based variational auto-encoder [71]. In its architecture shown in Fig. 3(c), the proposed recurrent based variational auto-encoder allows time-series modeling for progressive refinement and spatial attention in the shifted tensor inputs. Using progressive refinement, the deep network simply breaks up the joint distribution over and over again in several steps resulting in a chain of latent variables. This gives the capability to sequentially output the time-series data rather than compute them in a single shot. Moreover, a recurrent based variational auto-encoder can potentially improve the generative process over the spatial domain. By adding time series in the model as tensors with shifted data points, we can reduce the burden of complexity by implementing improvements over small regions of the tensor input at a time instance (spatial attention).

With these mechanisms, we achieve reduction of the complexity burden that an auto-encoder has to overcome. As a result, using a recurrent based variational auto-encoder allows for more generative capabilities that can handle larger, more complex distributions such as those in the given social game time series. Our models were tested in several sets of data from individual occupants and was highly capable of randomly generating new data with extraordinary similarities to the training data. This fantastic result provides a powerful tool for generating new data on top of the existing data and provides more flexibility in the application of the data in several real scenario mechanisms like demand response.

5. Experimental results

We now present the results of the proposed utility learning method applied to high-dimensional data collected from the social game experiment in the Fall 2017 and Spring 2018 semesters. As previously described, our data set consists of the per-minute high-dimensional data of occupant usage across several resources in their rooms. We evaluate the performance of utility learning under two characteristic scenarios. The first scenario involves having full information from the installed IoT sensors for performing "step-ahead" predictions. In this scenario, IoT sensors are continuously feeding information from the previous actions of the occupants. For the second scenario, referred to as "sensor-free", we stop taking into account the IoT sensor readings in each room. In the second instance, the aggregated past features of the occupants are missing. For this case, we have a model in which we use only features that we can acquire from external weather conditions (e.g. from a locally installed weather station), information about occupant engagement with the web portal, and seasonal dummy variables. All of these features are much easier to acquire without needing to keep the highly accurate but expensive IoT devices. The broader purpose of our proposed gamification approach is the development of exceptional forecasting models representing dynamic occupant behavior. As illustrated in Fig. 1(a), the building level energy usage prediction is fed to upper level components of the smart grid at the provider or microgrid level. In a real application scenario, the proposed building level modeling opens new avenues for demand response programs, which can incorporate real-time predictions of building occupant energy patterns. The proposed game theoretic models and iterative incentive design mechanisms are powerful in the sense that they can simultaneously be used to predict but also to incentivize desirable human behavior. Adaptive incentive design motivates building occupant energy efficiency through gamification platforms while accurately predicting their energy usage in order to feed it back to the higher provider levels of our framework.

[8] https://energyplus.net.

From our experiment, we present estimation results for the complete data set in both Fall and Spring versions of the experiment for two characteristic occupants. Both occupants have ample data for all of the relevant resources being considered. We used the first four game periods for the training of our models:

- Fall: Sep. 12th, 2017 - Nov. 19th, 2017 ($n = 100, 800$); Nov. 20th, 2017 - Dec. 3rd, 2017 ($n = 20, 160$).
- Spring: Feb. 19th, 2018 - Apr. 22nd, 2018 ($n = 90, 720$); Apr. 23rd, 2018 - May 6th, 2018 ($n = 20, 160$).

Before we trained our benchmark classifiers, we applied the mRMR algorithm to the total data set (data from all occupants) in the training period. This accounts for almost 4 million distinct data points in the Fall semester data set and 2.5 million distinct data points in the Spring semester data set. Applying mRMR results in several top features in both the Fall and Spring semester data sets. Interestingly, mRMR included several external features in the top relevant feature candidates. In particular, the presence of external humidity as an important feature for the ceiling fan is a good demonstration of the mRMR algorithm's capability to extract salient features. Moreover, features like survey points illustrate that some occupants co-optimized their resource usage while also trying to view their point balance, usage, and ranking in the game (e.g. visiting the web portal).

5.1. Forecasting via benchmark & deep learning frameworks

We have dual objectives in our leveraging of benchmark and Deep Learning frameworks. Our first objective is to achieve highly accurate forecasts of building occupant resource usage. Providers and retailers at the higher levels of Fig. 1(a) can integrate energy usage forecasts in demand response programs. Then, our second objective is to improve building energy efficiency by creating an adaptive model that learns how user preferences change over time and thus generate the appropriate incentives to ensure active participation. Furthermore, the learned preferences can be adjusted through incentive mechanisms [30] to enact improved energy efficiency (seen in the building level of Fig. 1(a)).

For learning optimal random utility models in the benchmark setting, we use the top twenty-five resulting features from the mRMR algorithm along with a pre-processing step of SMOTE with SVM initialization. Using SMOTE, we boost the accuracy of benchmark models due to the fact that our data set was heavily imbalanced. We achieve decent accuracy using well-trained benchmark models. Area Under the Receiver Operating Characteristic Curve is our forecasting performance metric. The AUC score quantifies the predictive behavior of a binary classifier by plotting the probability of true positive rate (i.e. correct classification of samples as positive) over false positive rate (i.e. the probability of falsely classifying samples as positive). All of the classifiers achieve decent AUC scores in both the Fall and Spring semester results, as shown in Table 1. In the "sensor-free" results, we have a significant drop in the achieved accuracy, but this is expected given that the IoT feed is decoupled. However, even in "sensor-free" examples we are able to predict occupant behavior using less representative features and having excluded the IoT sensors.

For the deep neural networks, we used training data resulting from the applied SMOTE step as in the benchmark analogy. We used two hidden layers of the feed-forward neural network, with 50% dropout and stochastic gradient descent method leveraging Nesterov's Momentum to accelerate convergence. Almost 20% of the training data was used as a validation data set for hyper-parameter tuning.

To further exploit the continuity of the sequential decision-making model, we experiment on the bi-directional deep recurrent neural network. We used a time sliding window—time step of two hours (120 distinct data points). We processed the data without being pre-processed from the SMOTE algorithm as we wanted to retain the underlying sequence of actions of the occupants (temporal dependencies of the data). We used three hidden layers with 60% dropout rate, and we applied an exponentially decaying learning rate (simulated annealing). In the training of bi-directional recurrent neural networks, we applied the principle of early stopping using a validation data set over the AUC metric. For our deep bi-directional networks, thirty-five epochs were optimal to be trained. As in deep neural networks, 20% of the training data was used as a validation data set for hyper-parameter tuning.

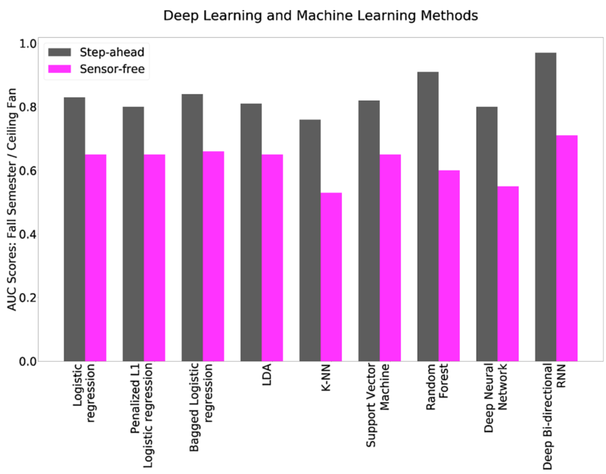
To evaluate the effectiveness of our proposed deep learning framework, we present the AUC scores of a representative example for comparison. From the results, it is clear that deep RNN outperforms the majority of alternative algorithms. One important remark is that deep RNN exceeds even when compared to Random Forest, which is considered a top-performing, robust classification model. Deep NN also achieved better performance in some examples over the Random Forest classifier, but this is not a general case. Fig. 4 introduces bar charts representing AUC scores for ceiling fan usage (on/off). Prediction results are divided into AUC scores for the two scenarios discussed previously—"step-ahead" and "sensor-free". Upon examination of these results, it is clear that deep RNN outperforms all other Deep Learning and machine learning models. Fig. 4 demonstrates that deep bi-directional RNN based models achieve accuracy almost equal to one. For more results, please refer to the archived version of this paper [51].

5.2. Generative models via sequential deep auto-encoders

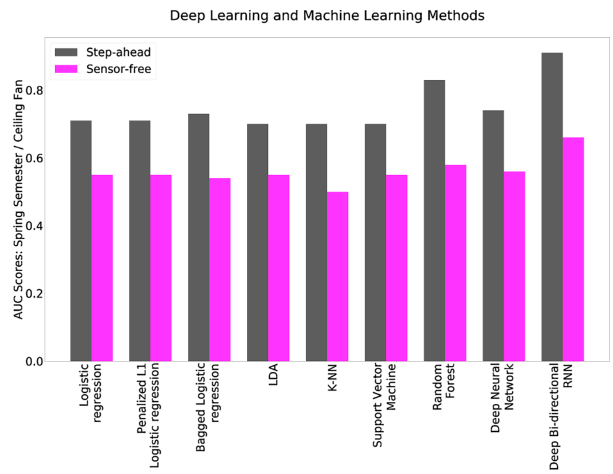
In Table 2, we present the results of two trained generative models using the full data set of a randomly selected occupant in the Fall semester. We trained both a conventional auto-encoder and a recurrent based auto-encoder. The resulting deep generative models can be used as a way to create simulations for mimicking building occupant behavior and preferences. This is an extra tool for quantifying variations in building occupant behavior as dynamic parts of a microgrid (seen in Fig. 1(a)). Generative models are capable of adapting to variations of the external weather conditions, which in turn creates an interesting view of building occupant energy usage patterns aligned with external

Table 1
AUC scores using Fall & Spring semester data towards "step-ahead"/"sensor-free" predictions.

	Fall semester			Spring semester			
"step-ahead"/"sensor-free"	Ceiling fan	Ceiling light	Desk light	Ceiling fan	A/C	Ceiling light	Desk light
Logistic regression	0.83/0.65	0.78/0.61	0.78/0.68	0.71/0.55	0.76/0.73	0.75/0.55	0.76/0.50
Penalized $l1$ Logistic regression	0.80/0.65	0.77/0.56	0.78/0.64	0.71/0.55	0.76/0.70	0.75/0.55	0.76/0.50
Bagged Logistic regression	0.84/0.66	0.80/0.59	0.79/0.68	0.73/0.54	0.73/0.73	0.76/0.54	0.79/0.51
LDA	0.81/0.65	0.78/0.58	0.74/0.68	0.70/0.55	0.73/0.73	0.75/0.55	0.70/0.51
K-NN	0.76/0.53	0.77/0.56	0.74/0.55	0.70/0.50	0.76/0.57	0.68/0.54	0.73/0.57
Support Vector Machine	0.82/0.65	0.78/0.60	0.76/0.68	0.70/0.55	0.75/0.73	0.75/0.55	0.70/0.50
Random Forest	0.91/0.60	0.78/0.59	0.98/0.63	0.83/0.58	0.83/0.65	**0.99**/0.54	0.96/0.50
Deep Neural Network	0.80/0.55	0.76/0.60	0.78/0.64	0.74/0.56	0.78/0.68	0.77/0.54	0.84/0.50
Deep Bi-directional RNN	**0.97/0.71**	**0.85/0.66**	**0.99/0.76**	**0.91/0.66**	**0.89/0.80**	**0.99/0.64**	**0.99/0.62**



((a)) AUC Scores using Fall semester data

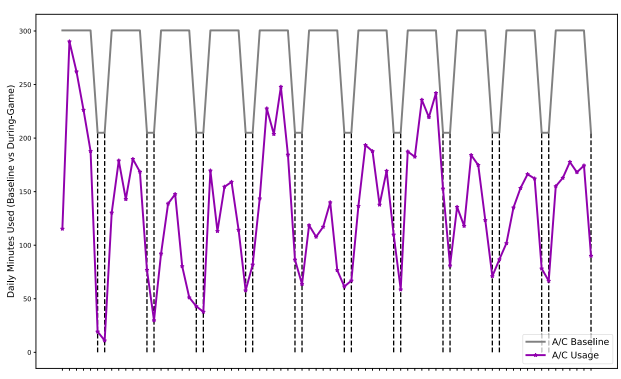


((b)) AUC Scores using Spring semester data

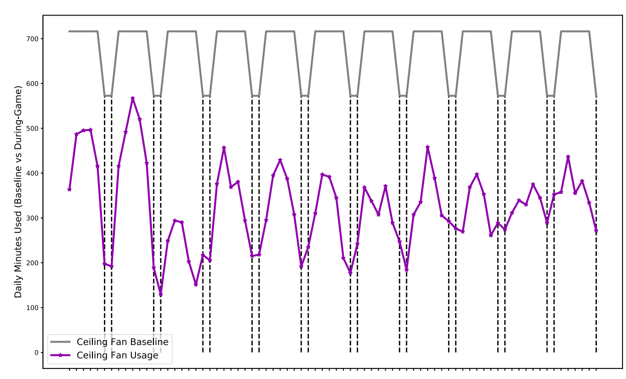
Fig. 4. Forecasting accuracy ("step-ahead"/"sensor-free" predictions) for ceiling fan usage (on/off).

Table 2
Feature comparison between proposed generative models (auto-encoders) using DTW score.

Time series feature	Conventional auto-encoder	RNN-based auto-encoder	p-values
Ceiling fan status (On/Off)	1.5e+04	**1.2e+04**	0.11
Ceiling light status (On/Off)	1.6e+04	**2.2e+03**	1.0
Desk light status (On/Off)	6.7e+03	**0.0e+00**	1.0
Dorm room temperature	1.3e+05	**1.2e+05**	0.0
Dorm room humidity	4.8e+05	**3.7e+05**	0.0
External temperature	1.0e+05	1.8e+05	0.0
External humidity	2.9e+05	4.3e+05	0.0



((a)) A/C daily average usage vs. baselines



((b)) Ceiling fan daily average usage vs. baselines

Fig. 5. Spring semester daily average minutes usage compared to weekday and weekend average baselines. Vertical black dashed lines indicate a weekend period.

weather patterns.

In Table 2, we present results for several selected features from the interior of a dorm room and from external weather data. For evaluating artificially generated time-series from the proposed auto-encoders, we utilize dynamic time warping (DTW), which measures the similarity between two temporal sequences—the ground truth and the artificial data [72]. In bold, we see that the recurrent based auto-encoder achieves a smaller DTW score in most of the features, leading to a generative model that isn't mimicking exactly or is deviating significantly from the original data set.

In efforts to evaluate the statistical significance of the calculated DTW scores from the recurrent based auto-encoder, we used a permutation hypothesis test. In this approach, we permute original and generated time-series, and we compute their DTW score looking for events that are more "extreme" than the one that is presented in Table 2. Interestingly, we have inside and outside weather based features (temperature and humidity) that have zero p-values, showing that the DTW scores using a recurrent based auto-encoder are statistically significant. For indoor device status features, however, p-values are large, indicating that the DTW score has high variability under the permutation test.

5.3. Energy savings through gamification

In this section, we present the resulting energy savings in both Fall and Spring semester versions of the social game. Our gamification framework introduces occupants to a friendly non-cooperative game and motivates reductions in their energy usage. Through the deployed IoT sensors and custom web portal, each individual building occupant received live feedback about their room's usage and their energy efficiency throughout the day. In Fig. 5, we present the average daily usage in minutes compared to average weekday and weekend baselines. The

Table 3
Hypothesis testing for Fall & Spring Game (before vs. after) from minutes per day usage.

Fall Semester	Weekday				Weekend			
Device	Before (Mean)	After (Mean)	*p*-value	Δ %	Before (Mean)	After (Mean)	*p*-value	Δ %
Ceiling light	417.5	393.9	0.02	5.6	412.3	257.5	0	37.6
Desk light	402.2	157.5	0	60.8	517.6	123.3	0	76.2
Ceiling fan	663.5	537.6	0	19.0	847.1	407.0	0	51.9
Spring Semester	**Weekday**				**Weekend**			
Device	Before (Mean)	After (Mean)	*p*-value	Δ %	Before (Mean)	After (Mean)	*p*-value	Δ %
Ceiling light	452.0	314.2	0	30.5	426.0	195.6	0	54.1
Desk light	430.1	104.6	0	75.7	509.4	81.5	0	84
Ceiling fan	777.4	541.6	0	30.3	847.1	331.8	0	60.8
Air con	469.8	225.8	0	51.9	412.3	81.8	0	80.2

vertical black dashed lines indicate a weekend period, which has a different corresponding average baseline target for the occupants. In terms of energy usage and savings, A/C and ceiling fan resources demonstrate an impressive reduction in usage, especially during weekends.

For quantifying the results, we employ hypothesis testing (A/B testing) using dorm occupant usage data before and after the beginning of the experiment. In Table 3, we see the hypothesis testing values for the different devices in both iterations of the experiment (Fall and Spring). In this table, the ”before” column denotes the data points gathered from before the game was officially started, while “after” is during the game period. Data points in the tables are bucketed in both weekday and weekend data and represent the average usage of all of the occupants. Usage is defined in minutes per day. In all of the devices, we have a significant drop in usage between the two periods. Drop in usage is given in the column named Δ %, and indicates reduction in the average usage of all of the participating occupants. The p-values resulting from the 2-sample t-tests show that the change in usage patterns is significant. Furthermore, we can see a much larger drop in usage is achieved over the weekends. These results are significant in that they demonstrate the capacity of our methods to optimally incentivize occupants in residential buildings to reduce energy usage.

6. Conclusion

This study presents a general framework for utility learning in sequential decision-making models. We leveraged several Deep Learning architectures and proposed a novel sequential Deep Learning classifier model. We also introduced a framework that serves as a basis for creating generative models, which are ideal for modeling and simulating human-building interaction toward improving energy efficiency. To demonstrate the utility learning methods, we applied them to data collected from a smart building social game where the goal was to have occupants optimize their room's resources. We were able to estimate several agent profiles and significantly reduce the forecasting error compared to all benchmark models. The deep sequential utility learning framework outperformed all other models being considered, and it improved prediction accuracy to an extraordinary degree in specific examples.

This last result shows that a Deep Learning architecture that handles a sequential data process has the effect of improving the overall accuracy. In this application we apply these methods specifically to smart building social game data; however, it can generalize to other scenarios with the task of inverse modeling of competitive agents, and it provides a useful tool for many smart infrastructure applications where learning decision-making behavior is crucial. Under our gamification application, occupants were highly motivated to drastically reduce their energy impact. This result is even more significant considering the fact that no effort was directed toward optimizing the incentive design for encouraging energy efficient behavior. Hence, research in optimal incentive design mechanisms should be pursued in the context of this work. Furthermore, special attention should be given to the management of pricing and how it affects the dynamics between the smart building and utility provider levels for applications like demand response programs. In general, we have demonstrated that our proposed framework can be used successfully for the purposes of accurately forecasting energy usage. However, Deep Learning models require a continuous feed of data and are not particularly robust to missing data points. This poses a challenge to many real-world applications, especially in such cases that might result in IoT sensors losing connection. Hence, we identify this as a limitation that should be addressed for our assumed Deep Learning models. Despite these constraints, we have shown that our implementation of a gamification approach to human-building interaction in smart infrastructure offers tremendous opportunities for improving energy efficiency and smart grid management.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found, in the online version, at https://doi.org/10.1016/j.apenergy.2018.12.065.

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