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Residential Consumer-Centric Demand Side Management

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***Abstract*—Energy Management Systems (EMS) are mainly price driven with minimal consumer interaction. To improve the effectiveness of EMS in the context of demand response, an alternative EMS control framework driven by resident behavior patterns is developed. Using hidden Markov modeling techniques, the EMS detects consumer behavior from real-time aggregate consumption and a pre-built dictionary of reference models. These models capture variations in consumer habits as a function of daily living activity sequence. Following a training period, the system identifies the best fit model which is used to estimate the current state of the resident. When a request to activate a time-shiftable appliance is made, the control agent compares grid signals, user convenience constraints, and the current consumer state estimate to predict the likelihood that the future aggregate load exceeds a consumption threshold during the operating cycle of the requested device. Based on the outcome, the control agent initiates or defers the activation request. Using three consumer reference models, a case study assessing EMS performance with respect to model detection, state estimation, and control as a function of consumer comfort and grid-informed consumption constraints is presented. A tradeoff analysis between comfort, consumption threshold, and appliance activation delay is demonstrated.**

***Index Terms*—Residential demand side management, energy consumption scheduling, activity recognition, energy management system, Hidden Markov models.**

I. Introduction

DEMAND response programs would benefit significantly from residential sector penetration. This sector alone consumes 22% of US total energy [1] and is growing rapidly. From 1980-2009, residential electricity consumption increased by 57.2% due to housing and population growth alone [2]. For programs representing 17% of demand response potential, residential participation has the impact to provide a 45% reduction in peak loads [3].

However, only 10% of residents enroll in demand response programs and even fewer are compliant [4]. These programs require involuntary or voluntary participation of consumers in exchange for utility-provided monetary incentives. Involuntary automated demand response (AutoDR) gives direct control to the utility enabling it to clip peaks in demand for discretionary loads associated with heating and cooling in exchange for rebates. However, the acceptance of such systems are low as residential consumers are unlikely to give up autonomy of their homes to the utility. In contrast, voluntary programs using Advanced Metering Infrastructure (AMI) rely on consumer compliance to grid alerts and pricing strategies to manually shift loads to off-peak hours preserving resident autonomy at the expense of convenience. For example, to make informed appliance scheduling decisions, the user must examine their energy bill, understand their aggregate power consumption, maintain an active knowledge of contributing appliances, and be aware of outside grid conditions. Utility pricing strategies such as time of use (TOU) pricing, dynamic pricing (DP), and critical peak pricing (CPP), further complicates user load shifting decision-making.

Energy Management Systems (EMS) offer a partial solution to obstacles in current residential demand response programs. These systems utilize the convenience of automated demand response without compromising residential autonomy. Such systems, validated through simulated case studies, assume pricing as a driving factor for residential consumption behavior and measure consumer satisfaction indirectly through utility function parameters [5]–[8]. In other words, EMS methods are constructed from various cost-benefit analyses to shift loads to times corresponding to minimal cost. If successfully integrated to the residential sector, price driven energy management would shift many consumer loads to off-peak times. Thus, instead of flattening the residential sector consumption peak, scheduling could potentially result in a shift in the original peak with respect to time. In this scenario, load peaks would remain unchanged and utility pricing schemes would be adjusted to take into account popular demand.

The effectiveness of price-driven energy management frameworks would benefit by including consumer behavior as a variable in the optimization of "shiftable" appliance scheduling. Pricing as a reward for energy curtailment has shown to wear off with time in other behavioral domains. Furthermore, the sustainability of monetary incentives is unclear for the long term, which could potentially result in a rebound in demand behavior exceeding pre-program levels should these incentives no longer be provided [4]. It becomes necessary to examine the source of demand–the individual consumer. Residential consumer behavior must be examined to predict habitual consumption patterns, improve existing EMS scheduling algorithms, and provide user feedback with respect to consumption as a function of behavior.

Inclusion of the consumer as part of EMS framework

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presents challenges due to the nonlinearity and complexity of human behavior. To address this we take a specific human behavior modeling approach to build a system that directly includes the resident in the system feedback loop to drive the scheduling of appliances. Similar to proposed EMS, the improved EMS shift loads, but does so dynamically–providing the individual consumer with a unique real-time load control mechanism as a function of behavior. In contrast to offline data driven activity pattern discovery, this method requires prebuilt models facilitating dynamic recognition of daily activity sequences sufficient for the appliance scheduling control.

In this paper we make the following contributions to existing energy management system frameworks:

- Given a household appliance inventory, we build a dictionary of reference models for a single residence as a means of detecting structured general behavioral activity from real-time AMI aggregate consumption observations outlined in Section IV.
- In Section V we dynamically detect resident behavior sequences and patterns from AMI aggregate consumption during a training period whereby the best fit reference model is identified. Following training, the EMS can estimate the current behavioral states as a function of the current consumption.
- For an appliance activation request, we implement appliance scheduling using an activity informed "on-off" control mechanism. The EMS interfaces with AMI to receive real-time DR consumption constraints, predicts the likelihood of exceeding these constraints based on the current user state, best fit model, requested appliance, user convenience, and current electric load. The algorithmic framework is introduced in Section VI.
- In Section VII we perform a case study instantiating the improved EMS to schedule a continuous cycle deferrable appliance load and assess the performance in terms of appliance activation delay and user comfort.

II. Related Work

Current work in residential demand-side management focuses on peak load reduction through load shifting. Load shifting techniques emphasize appliance scheduling on a single residence or on multiple residences using home energy management systems (EMS) that take advantage of two-way communication between the home and the grid. EMS agents present an interesting model predictive control application since they must schedule appliance loads subject to constraints defined by the optimization framework. Depending on the scale, the framework can be centralized or distributed. On a neighborhood level, each individual user may define preferences by setting appliance operating modes and activation times which can be compared to the total energy cost set by the utility as a function of market demand [9]. Since the centralized problem requires extensive information of individual user appliance preferences and energy cost as a function of the scheduling preferences of all neighborhood users, the solution to this type of problem is non-trivial. [10] discusses the limitations of centralized methods in terms of computational complexity and incentive compatibility offering a distributed mechanism that takes into account day-ahead allocation as well as individual real-time consumption in the scheduling of appliances by EMS agents. The distributed optimization framework allows the problem to be convex under the free market assumption that utility pricing will drive user self-interest thereby decreasing grid operational costs.

However, the focus on user self-interest as pertaining primarily to cost minimization and comfort defined by appliance operation, does not take into account the variability in demand due to human daily behavior. For example, [11] derive energy consumption scheduling algorithms using Nash equilibrium to minimize cost and peak to average ratio by deferring "shiftable" appliance loads as an alternative to changing resident energy consumption. Though simulation results successfully show a reduction in overall consumer cost, consumer satisfaction outside of cost and appliance duration parameters are not assessed. Similarly, [6] develops an energy management model using coevolutionary particle swarm optimization to schedule "must-run" resistive loads as well as loads associated with PHEVs, temperature systems, and pool pumps. In this framework, the consumer must define the monetary benefit of a unit of energy usage as a means of quantifying personal comfort based on ambient and water temperatures as well as PHEV charge. These parameters then determine the cost of "undelivered services" taking into account acceptable temperature gradients, water discharge, PHEV discharge under the constraint of tariffs set by the utility. However, in practice, user engagement in defining the "utility" of specific optimization constraints as an indirect parameter of comfort may not be straightforward. Automatic detection of user comfort constraints offers an improved solution but is subject to variability. In [12] appliance cluster scheduling based on time of use probabilities and type is demonstrated under three different pricing constraints. Scheduling is only considered for interruptible pre-emptive devices under dynamic pricing, feed-in tariffs, and net sale-net purchase energy programs. In this formulation, appliance time of use probabilities are approximated over a constant schedule in an off-line manner and do not take into account how appliance time of use changes on a daily basis. In fact, [13] showed that appliance times of usage presented a key challenge to effective learning of appliance operating characteristics as they presented several behavioral regimes. In other words, appliance behavior varied depending on the household, time of day, and make and model. For example, the duty cycle of the tumble dryer is a function of size and composition of load. While [13] demonstrated a means of learning household characteristics by learning appliance behavior, their work emphasized the need to learn higher level human behaviors driving appliance usage as an improvement to current art.

Research combining behavioral sciences and demand response are limited to offline studies based on data mining of survey or testbed sensor data to gain insight on human activities and identify patterns in sensor data [14]. [15] developed hierarchical activity graph based models using American Time Use Survey (ATUS) and Residential Energy Consumption Survey (RECS) statistics dependent on num-

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ber of household members, gender, age, employment and time. [16] estimated comfort requirements for optimization of schedules via information from GPS, social media, and load patterns. Using two smart home testbeds fitted with motion, temperature, water temperature, stove, and power line sensors, resident activity as a function of sensor triggering was found to be directly proportional to energy consumption [17]. While [17] used demand to determine human behavior, studies utilizing behavior to determine demand and schedule loads have been relegated to case studies on specific distributed energy resources or on passive visual energy feedback. In [18], using testbed data from [17] and [19], a case study to find optimal battery charging and discharging is demonstrated successfully supporting a justifiable need for further behavior based demand response study.

Since demand is a function of behavior, accurate load prediction requires the use of robust human behavioral models which can be used in algorithms to recognize and differentiate individual activities at a given time. While not a direct focus in demand response applications, human behavior recognition has been a significant topic of interest in artificial intelligence applications. Though human behavior is nonlinear in nature, activity recognition methodologies allow for identification of informative features in daily consumption patterns. State-model based approaches discretize human behavioral routines as a model based on a finite activity state space and use statistical methods to train the model indirectly through observations. The models are then evaluated by calculating the likelihood that a given model has generated the sequence of observations [20]. Evaluation is conducted using the maximum likelihood estimate or the maximum a posteriori probability [21]. In particular, Hidden Markov Models (HMMs) provide a natural probabilistic framework to represent resident behavior as it has been used extensively in human driven applications such as surveillance, gesture based human computer interfaces, and patient monitoring [21]. Additionally HMMs allow for general models to be built from observations which are a function of complex human behaviors. In [22], [23] general models built from training sets, were able to discriminate between human activities from test data to accuracies above 81%, and 91% respectively.

Taking into consideration the success of dynamic activity recognition models, we build upon previous work to improve energy management systems (EMS) with high level behavioral activity as the driver of resident consumption. While understanding human activity is not the goal of this study, identifying activities which directly impact home energy usage enables the resident control agent to optimally schedule appliances according to the user in relation to demand response programs.

III. Energy Management System (EMS)

The EMS is an intelligent automated control agent that dynamically learns consumer behavior, analyzes and predicts future behavior, and schedules and controls appliances with respect to behavior and grid signals. Central to the system is the resident energy consumer. Their habits and activities of daily life are what drive their consumption profile. It therefore becomes imperative for the intelligent agent to learn typical user behavior based on patterns in load profiles. The system does so by comparing sensed electricity consumption to pre-built general consumer models and prior information with respect to the inventory of appliances in the home. Following a training period and successful dynamic model detection, the agent continues to receive consumption information allowing the system to estimate current and future resident states based on the model. However, decoding consumer activity alone is not the objective of the EMS. The goal of the EMS is to perform appliance scheduling based on current *consumer activity*, *appliance* energy requests, *grid signals*, and user *convenience* parameters. The system thus serves to interface between complex systems in order to make decisions with respect to the activation of cyclic "shiftable" loads to improve residential consumer demand response.

Consumer Activity: Human behaviors exhibit hierarchical structure according to goals and recursive implementation of sub-goals [24]. In the home, activities of daily life drive energy consumption dictating which appliance will be initiated at any given time. Realizing the significance in encoding hierarchy, we propose a modeling framework that captures dependencies between finite human activity units and appliances. In other words, we can simplify residential behavior into sequences of activity states that cannot be directly measured. For example, activity states such as *hygiene*, *cook*, *clean*, or *rest* each have unique effects on consumer load profile as well as which appliances may be activated. Different sequences of activities characterize user schedules and provide a basis for building a dictionary of typical consumer models used by the EMS to detect daily user behavior and make scheduling decisions.

Appliances: Each consumer activity influences appliance usage. For example, if a user is *cleaning*, they are likely to use appliances such as a vacuum, a washing machine, or a steamer. Given the inventory of household devices, we capture these dependencies by grouping short operating appliances according to their most likely activity. Doing this allows us to compress the state space of these "on-off" appliances by activity. Larger appliances that have longer operating periods are classified as either "shiftable" or "non-shiftable" activity independent or dependent long-term devices. These devices may operate over multiple behavior activities and cannot be compressed in state space. In fact, the EMS seeks to control and schedule "shiftable" larger appliances due to their heavy influence on load profile. We then build a table of all possible combinations of compressed activity-short-term-appliance grouping as well as the uncompressed larger appliance states, allowing us to characterize activity influenced consumption load profiles.

Grid Signaling: Consumption constraints are taken as an input to the control agent directly from the AMI. These constraints may be consumption restrictions (kWh) placed in the form of an alert or as a function of TOU or dynamic pricing (DP) schemes. The EMS takes into account the constraint when making scheduling decisions.

Consumer Convenience: The resident may also set a convenience constraint with respect to the activation delay of "shiftable" appliances should the grid constraint be strictly

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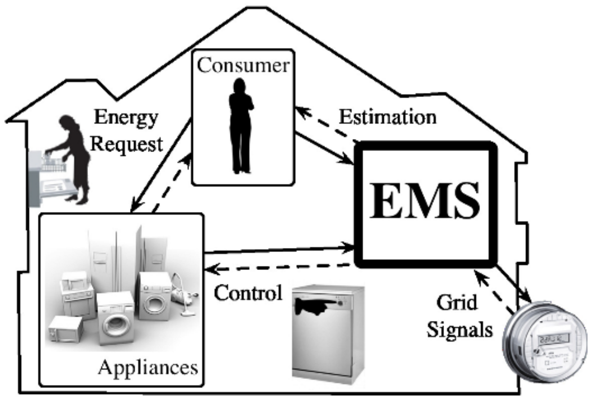

Fig. 1: Consumer-centric Energy Management System

met. Depending on the current activity of the user, deferring loads to a later time based on grid conditions alone may be undesirable. Thus, consumer constraints allow the user to have a degree of freedom with respect to appliance scheduling without having to override the energy management system.

To understand how consumer activity, appliances, grid signaling, and consumer convenience interact in the EMS, one may consider the case where a resident makes an energy request for the activation of a heavy "shiftable" appliance. At the instant of the request, the EMS retrieves the present aggregate consumption as well as grid signals from the AMI. Given that the best fit behavioral sequence has already been detected, the EMS can predict future consumption states based on activity-dependent load inferences and compare these states to grid signals. The EMS calculates the likelihood that the additional requested load results in residential consumption in excess of the grid signal constraint for the duration of the requested appliance operational cycle. If the likelihood of the exceeding the grid signal is within an additional parameter defined by the user, the appliance is scheduled to run. If not, the load is deferred as the system waits for the next available time trial and AMI power consumption observation.

IV. Stochastic Model

We can build a hierarchical model for the consumer as a vector-valued homogeneous Markov chain that includes activity and individual home appliance random variables corresponding to activity-appliance combinations discussed in Section III. The Markov chain, by definition, is discrete in time and assumed to be discrete in state-space. Components of the vector valued chain are also assumed to behave Markovian. Each individual random variable used to construct the model is presented and summarized in Table I.

A. Consumer Activity

We define a categorical random variable A of consumer activities as a homogeneous Markov chain, discrete in time and discrete in space $A{=}\{A_t{=}a_i, t, i{\in}\mathbb{N}^+\}$ where t is time, and a_i is an activity label from a finite set of outcomes in the state space $\mathcal{S}_A$. These activity labels or states include activities of daily living such as *dressing*, *dining*, etc. Since A is a temporal process representing a sequence of daily living activities, we structure A as a "left-right" non-ergodic (Bakis) chain where the state index increases or stays the same as time increases. A is described by the transition matrix $P\left(A_{t+1}|A_t\right)$ which has the characteristics of being a $\max(\mathcal{S}_A) \times \max(\mathcal{S}_A)$ diagonal band sparse matrix with an absorbing terminal state $a_{\max(\mathcal{S})}$. The sequences of A are based on permutations of activities without repetition. These sequences terminate on particular activities (i.e. *sleep* or *leave*) to differentiate between times of day. For example, in the morning a consumer may wake up to perform *hygiene* tasks, *dress*, and *leave* for work, where *leave* represents the end of the morning sequence. Possible repeated activities such as *hygiene* or *dress* are enumerated and may have different permanence times described by self-looping probabilities in the Markov transition matrix of A which are adapted from [25], [26], and [15].

TABLE I: Model Random Variables and Parameters

Random Variable	State Description	Parameters
A	daily activity	$P(A_{t+1}\|A_t)$
V^l	short-term appliance	$P\left(V^l_{t+1}\|V^l_t\right)$
C	$\sum_{l\in\mathcal{S}_{V^l\|A}} V^l_t$	$P(C_{t+1}\|C_t, A_t{=}a_i)$
E	shiftable appliance	$P\left(E_{t+1}\|E_t, A_t\right)$
F	non-shiftable appliance	$P\left(F_{t+1}\|F_t\right)$
Z	$Z_t = [A_t, C_t, E_t, F_t]^\top$	$P(Z_{t+1}\|Z_t)$
X	aggregate consumption	$X_t{=}C_t{+}E_t{+}F_t$

B. Taxonomy of Appliances

In accordance with the work presented in [11], we describe a taxonomy of the types of appliances present in the home.

- Activity-dependent short-term appliances
- Activity-dependent long-term "shiftable" appliances
- Activity-independent long-term "non-shiftable" appliances

We construct individual appliance Markov chains for each type based on the quantized Watt value of individual operating modes respectively. In other words, for a specific appliance, we identify discrete states based steady-state power consumption levels from sub-metered appliance curves and manufacturer specifications. Operational start and end times for each appliance are built in the Markov chain transition matrix. State transitions are estimated based on the frequency of transitions from one power level to another relative to the total number of transitions from the power level under consideration as demonstrated in [27].

Dependent Short-term Appliances: We define a random variable V^l, where $1 \leq l \leq L$ represents each short-term activity dependent device, with L total short-term appliances present in the home. $V^l = \{V^l_t = v_j, j, k, l{\in}\mathbb{N}^+\}$, described by the transition matrix $P\left(V^l_{t+1}|V^l_t\right)$ and state space $\mathcal{S}_{V^l}$. v_j, the state of V^l_t at any given time trial, is equal to the consumption value for the state of appliance l. We may partially

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build the vector-valued Markov chain for short-term appliances that depend on activity A as $[A_t{=}a_i, V_t^1{=}v_i^1, \ldots, V_t^L{=}v_i^L]^\top$, where $t{\in}\mathbb{N}^+$ and $a_i{\in}\mathcal{S}_A$, $v_i^1{\in}\mathcal{S}_{V^1}$, and $v_i^L{\in}\mathcal{S}_{V^L}$. Short-term activity dependent devices are activated during specific behavioral activities. For example for the activity *cook*, the appliances stove, oven, toaster, coffee maker, blender would constitute short-term activity dependent appliances. While for the activity *workout*, dependent appliances would include the treadmill, elliptical machine, or stationary bicycle. However, for a large inventory of short-term devices, the vector-valued Markov chain grows quickly in complexity. In this context, as the number of appliances increase, the number of individual device states corresponding to consumption level increase directly affecting transition matrix dimensions as well as the number of mathematical operations used to calculate the forward probabilities described in Section V. Complexity also becomes an issue when individual devices are assumed to operate with activation dependencies, as is the case with an entertainment system. In this example, turning on the television may also turn on the sound system, recording device, and the game console, requiring additional activation sub-chains to be encoded in the system model. For these appliance clusters, the state space can quickly become intractable. To alleviate complexity we note that the sum of the V_t^l for a time slice and affiliated activity results in a short-term appliance aggregate consumption. This allows us to compress the state space by defining the partially defined vector-valued Markov chain in terms of the random variable C, where we assume:

$$C_t{=}\sum_{l\in\mathcal{S}_{V^l|A}} V_t^l, \tag{1}$$

where $\mathcal{S}_{V^l|A}$ is the set of appliances involved in the activity. We can solve to get the elements of the transition matrix of C for a particular $A{=}a_i$ by $P(C_{t+1}, A_{t+1}{=}a_i|C_t, A_t{=}a_i){=}P(C_{t+1}|C_t, A_t{=}a_i)$

$$=P\left(\sum_{l\in\mathcal{S}_{V^l|A}} V_{t+1}^l, A_t{=}a_i|\sum_{l\in\mathcal{S}_{V^l|A}} V_t^l, A_t{=}a_i\right) \tag{2}$$

$$=\sum \prod_{l\in\mathcal{S}_{V^l|A}} P(V_{t+1}^l|V_t^l) \tag{3}$$

for a given activity $A = a_i$. Since we compress the state space by taking into account clusters of activity-dependent appliances defined by aggregate power consumption, appliance activation dependencies for a specific activity have no net effect, allowing us to achieve the same system model as when the devices are assumed to activate independently. When $A_{t+1}{=}a_j \neq A_t{=}a_i$ we use the stationary distribution

$$\lim_{n\to\infty} \frac{1}{n} \sum_{m=1}^{n} P(C_m, |C_0, A_0{=}a_j) \tag{4}$$

as the initial distribution of moving into the new activity and appliance dependencies. The state space $\mathcal{S}_C$, is defined by states c_j, where $j = \{1, \ldots, \prod_{i=l}^{L} \max \mathcal{S}_{V^i}\}$

Dependent Long-term "Shiftable" Appliances: We are interested in scheduling these appliances with our control agent. "Shiftable" otherwise known as deferrable loads are characterized by long operational cycles, high load profiles, and function without interruption once activated. These appliances are dependent on activity A. Examples of "shiftable" activity-dependent loads are the washing machine and the dishwasher which are likely initiated when the user is in the activity state "clean." In our model we define these loads as $E{=}\{E_t{=}e_m, k, m \in \mathbb{N}^+\}$, described by the transition matrix $P(E_{t+1}|E_t, A_t)$ and state space $\mathcal{S}_E$. The transition matrix is characterized by the operation time spent in each power state. Once initiated for an activity sequence, a memory variable is toggled between 1 and 0 to keep track of a finished appliance cycle. These appliances are not included in the vector-valued chain, but the "shiftable" appliances that the user may not seek to control, are included. For generality, we will include a "shiftable" appliance for both the controlled and uncontrolled case.

Independent Long-term "Non-shiftable" Appliances "Non-shiftable" or non-deferrable loads are loads which operate irrespective of the activity and are essential for the proper function of the home. For example a refrigerator must always be on to ensure the safety and quality of food for the inhabitant. These loads are not controlled by the energy management system as they must operate at all times. $F = \{F_t = v_t, k, n \in \mathbb{N}^+\}$, is described by the transition matrix $P(F_{t+1}|F_t)$ and state space $\mathcal{S}_F$.

C. The Complete Model

We now proceed to define the model in its entirety, based upon the definitions of random variables A, C, E, and F. The vector-valued Markov chain $Z_t{=}[A_t{=}a_i, C_t{=}c_i, E_t{=}e_i, F_t{=}f_i]^\top$, where $t{\in}\mathbb{N}^+$ represents the hidden state and the observation $X_t{=}C_t{+}E_t{+}F_t$ is the aggregate residential consumption. To fully characterize the HMM transition matrix $P(Z_{t+1}|Z_t) = P(A_{t+1}, C_{t+1}, E_{t+1}, F_{t+1}|A_t, C_t, E_t, F_t)$ we use the chain rule.

For $A_{t+1}{=}A_t$, $P(Z_{t+1}|Z_t){=}$

$$P(A_{t+1}|A_t)P(C_{t+1}|C_t,A_t)P(E_{t+1}|E_t,A_t)P(F_{t+1}|F_t). \tag{5}$$

For $A_{t+1}{\neq}A_t$, $P(Z_{t+1}|Z_t){=}$

$$P(A_{t+1}|A_t)\Pi_C(i, A_{t+1})\Pi_E(j, A_{t+1})P(F_{t+1}|F_t), \tag{6}$$

for $1{\le}i{\le}\max(\mathcal{S}_C)$ and $1{\le}j{\le}\max(\mathcal{S}_E)$. Π_C and Π_E are the initial distribution of the aggregate consumption of the short-term activity dependent appliances and the initial distribution of the single activity dependent "shiftable" long-term appliance. The element-wise initial distribution of the HMM is

$$\begin{aligned}\Pi_{Z_1}{=}&\Pi_{A_1,C_1,E_1,F_1}\\ {=}&\Pi_A(A_1{=}a)\Pi_C(i, A_1)\Pi_E(j, A_1)\Pi_F(k).\end{aligned} \tag{7}$$

for $1{\le}a{\le}\max(\mathcal{S}_A)$, $1{\le}i{\le}\max(\mathcal{S}_C)$, $1{\le}j{\le}\max(\mathcal{S}_E)$, $1{\le}k{\le}\max(\mathcal{S}_F)$. The emission matrix is defined as:

$$P(X_t|Z_t) = P(X_t|A_t, C_t, E_t, F_t). \tag{8}$$

The emission matrix is built by identifying which combinations of C_t, E_t, and F_t result in the observation

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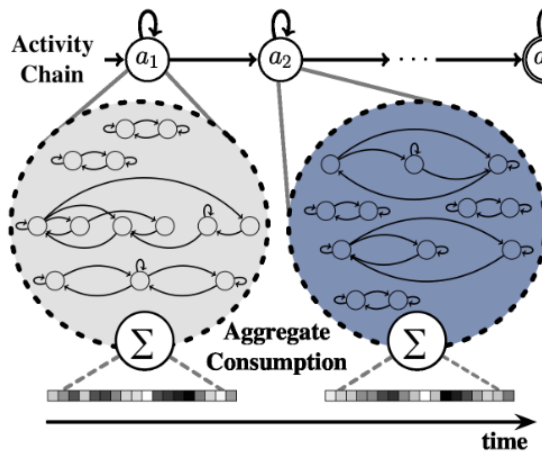

Fig. 2: Activity appliance dependencies, including short-term,"shiftable," and "nonshiftable" loads which sum to the total consumption per time slice.

$X_t{=}C_t{+}E_t{+}F_t$. This matrix has dimensions of $\max(\mathcal{S}_Z) \times \max(\mathcal{S}_X)$.

V. Model and State Detection

The proposed energy management control agent operates by detecting and classifying the resident into a particular reference model λ_i defined by $(\Pi_Z^{(i)}, P(Z_{t+1}^{(i)}|Z_t^{(i)}), P(X_t|Z_t^{(i)}))$ for $1{\le}i{\le}\max(\mathcal{S}_{\lambda_i})$ from a dictionary of models based on the time of day, within a training period T. The set of possible models are derived from unique sequences of activities A corresponding to possible consumer schedules and employment demographics. Different sequences result in different activity transition probabilities, $P(A_{t+1}^{(i)}|A_t^{(i)})$, which are propagated to the calculations of $\Pi_Z^{(i)}, P(Z_{t+1}^{(i)}|Z_t^{(i)})$, and $P(X_t|Z_t^{(i)})$ used to define a specific λ_i as outlined in Section IV. Following the training period T, the identified model λ_i is used to calculate the maximum likely current joint state of total home appliances and activity Z_t which allows the system to predict the likelihood of future consumption observations for a rolling time horizon. The resulting load profile predictions inform real-time decisions with respect to the scheduling of "shiftable" loads in light of consumption limits defined by demand response and user comfort discussed in Section VI. In order to calculate the best fit reference model, λ_i for a consumer we utilize the forward algorithm for HMMs to calculate the posteriori probability based on a sequence of consumption observations during the training period T.

A. Consumer Model Detection

Given the observation sequence: $X_1{=}x_j, \ldots, X_T{=}x_z$, we may calculate: $\alpha_k(s){=}P(X_1{=}x_j, \ldots, X_T{=}x_z, Z_k{=}s)$ for a specific model λ_i defined by $(\Pi_Z^{(i)}, P(Z_{t+1}^{(i)}|Z_t^{(i)}), P(X_t|Z_t^{(i)}))$ or in matrix format: $(\mathbf{\Pi}_{\lambda_i}, \mathbf{P}_{\lambda_i}, \mathbf{B}_{\lambda_i})$. For the first time step we calculate the probability of the joint distribution of the first hidden state and consumption observation using the initial distribution of the hidden chain. $\alpha_1^{(i)}(s){=}P(X_1{=}x_j, Z_1^{(i)}{=}s) = \Pi_{Z_1}^{(i)}(s)P(X_1{=}x_j|Z_1^{(i)}{=}s)$, or

$$\alpha_1^{(i)}{=}\mathbf{\Pi}_{\lambda_i}^\top \cdot \mathbf{P}_{\lambda_i}. \tag{9}$$

We may generalize the remaining forward calculations for $1{\le}t{\le}T-1$ as

$$\alpha_{t+1}^{(i)}{=}\alpha_t^{(i)} \cdot (diag(\mathbf{B}_{X_{t+1}=x})_{\lambda_i}) \cdot \mathbf{P}_{\lambda_i}. \tag{10}$$

To classify the user we evaluate

$$\sum_{r \in \mathcal{S}_{Z^{\lambda_i}}} \alpha_T^{(i)}(r), \tag{11}$$

where T is the training period. The model λ_i that results in the maximal value is then identified as the approximate user reference class based on the sequence of real-time observations sensed by the system.

B. State Estimation based on Model

Once a reference class for a sequence of training observations $X_1{=}x_j, \ldots, X_T{=}x_z$, is determined ($\lambda_i{=}\lambda$), the state estimate may be calculated by propagating the forward a posteriori probability value for the new real-time consumption observations using the statistics, $(\mathbf{\Pi}_\lambda, \mathbf{P}_\lambda, \mathbf{B}_\lambda)$, of the reference class. Since we have identified the best fit model according to the resident's consumption, we drop the λ_i in our notation in this section to increase readability. We can scale the forward joint probability value to obtain a distribution of states. In other words, given the sequence $X_{T+1}{=}x_a \ldots, X_t{=}x_b$ we are interested in calculating

$$P(Z_t{=}s|X_{T+1}{=}x_a, \ldots, X_t{=}x_b){=}\frac{\alpha_t(s)}{\sum\limits_{r \in \mathcal{S}_Z} \alpha_t(r)}. \tag{12}$$

The state $Z_t{=}s$ that results in the greatest probability given the observation sequence is defined as the maximum likelihood estimate.

VI. Control

An "on/off" appliance control algorithm is developed based on consumer classification and the current hidden state estimate to determine the soonest available time slice to schedule "shiftable" must-run loads under consumption and user-defined constraints.

A. Grid Signals

We represent a consumption constraint z, a maximum Watt value, which may be a function of utility pricing programs or grid alerts. To schedule a deferrable load we must compare the sensed current user consumption, X_t, with the constraint as well as the energy use profile of the deferrable load itself. In this scheme, the "shiftable" load profile is deterministic as it follows a defined operational cycle, d_t, for $1 \le t \le N$ upon activation. We are interested in calculating:

$$P(X_t \ge z - d_t),$$

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which corresponds to the joint state $Z_t{=}(A_t, C_t, E_t, F_t)$ for the combinations of C_t, E_t, F_t that produce a total wattage in excess of the consumption constraint $z - d_t$. We can thereby partition the state space of Z_t into two sets, the "taboo" set, H_Z corresponding to $X_t = C_t + E_t + F_t \geq z - d_t$, and its complement H_Z^c. We then rearrange the states of $P(Z_{t+1}|Z_t)$ to the following format:

$$P(Z_{t+1}|Z_t) = \begin{bmatrix} \mathbf{T_Z(1,1)} & \mathbf{T_Z(1,2)} \\ \mathbf{T_Z(2,1)} & \mathbf{T_Z(2,2)} \end{bmatrix} \qquad (13)$$

where $\mathbf{T_Z(1,1)}$ represents the sub-matrix of states which transition from $H_Z^c{\to}H_Z^c$, $\mathbf{T_Z(1,2)}$ represents the sub-matrix of states which transition from $H_Z{\to}H_Z^c$, $\mathbf{T_Z(2,1)}$ represents the sub-matrix of states which transition from $H_Z^c{\to}H$, and $\mathbf{T_Z(2,2)}$ represents the sub-matrix of states which transition from $H_Z{\to}H_Z$ [28].

The total probability of transitioning from H_Z^c to the set H_Z within a finite time horizon, N, defined by the operational cycle of d_t, can be calculated using the sub-matrices of the rearranged transition matrix as

$$P_{\mathbf{T_Z(1,2)}}(N) = \sum_{s\in\mathcal{S}_H}\sum_{n=1}^{N}\mathbf{T_Z(1,1)}^{n-1} * \mathbf{T_Z(1,2)}. \qquad (14)$$

This probability provides the energy management system a means of predicting the user consumption profile for a finite time horizon, N, as well as a probability measure as with respect to the consumption constraint.

B. User Convenience

We can further implement an additional degree of freedom over the control of scheduling by taking into account user convenience defined by q which is a constraint placed on the probability of transitioning from H_Z^c to the set H_Z within the operational cycle of the appliance we seek to control. In other words, the consumer convenience constraint allows the user to loosen the grid defined consumption constraint by allowing the resident consumption to hit states above threshold $z - d_t$ within a probability of q. In other words,

$$P_{\mathbf{T_Z(1,2)}}(N) = \sum_{s\in\mathcal{S}_H}\sum_{n=1}^{N}\mathbf{T_Z(1,1)}^{n-1} * \mathbf{T_Z(1,2)} \leq q \quad (15)$$

Thus, the user has the ability to tune the tradeoff between convenience and consumption threshold rules, affecting the resulting delay in activating the appliance.

C. Control Algorithm

We outline the control algorithm based on activity sequence detection from a library of typical user reference models, state estimation based on the detected model and current consumption, and the evaluation of energy requests constrained by grid signals and user convenience.

- A sequence of real-time resident consumption observations are input to the EMS via the "smart" meter. For a training period of T, we use the forward algorithm to calculate the a posteriori probability for a set of typical reference models λ_i. Following the training period, the model resulting in $\max(\sum_{r\in\mathcal{S}_{Z\lambda_i}} \alpha_T(r))$, is determined to be the closest approximate reference model.
- Based on the selected user model, we calculate the $\max(P(Z_t{=}s|X_{T+1}{=}x_a,\ldots,X_t{=}x_b)){=}\max\frac{\alpha_t(s)}{\sum_{r\in\mathcal{S}_Z}\alpha_t(r)}$ to find the maximum likely state of the hidden Markov chain, Z_k for X_k following the training period.
- The consumer energy request $R_k = r$ where $r \in \{0,1\}$ is dependent on the activity $P(R_k|A_k)$. $R_k = 1$, represents the request being made, while $R_k = 0$ is no request. For each sequence of consumption observations, the request, once made cannot be repeated for the next time trial or appliance. In other words, once $R_k = 1$, the request cannot be made again.
- Based upon R_k and the state estimate of Z_k at the time of the request k, we determine if the state $Z_k \in H_Z$. If it is in the "taboo" set we wait to update the state estimate for the next time trial until the state is no longer "taboo." Once $Z_k{\in}H_Z^c$, we find the total probability of hitting the set H_Z given that we started in a "safe" set.
- Activation of the appliance occurs when the total probability, $P_{\mathbf{T_Z(1,2)}}(N){\leq}q$ of hitting the set H_Z given that we started in H_Z^c.

VII. Numerical Results

We present the results of an EMS case study for an evening time of day sequence of activities comprised of one hundred fifty discrete time trials with each time trial representing a five minute interval. The individual activity A and the household inventory of short-term appliances V^l is presented in Table II. With the appliance inventory, the reference models, $\lambda_1{\sim}(\Pi_{Z^{(1)}}, P(Z_{t+1}^{(1)}|Z_t^{(1)}), P(X_t|Z_t^{(1)}))$, $\lambda_2{\sim}(\Pi_{Z^{(2)}}, P(Z_{t+1}^{(2)}|Z_t^{(2)}), P(X_t|Z_t^{(2)}))$, and $\lambda_3{\sim}(\Pi_{Z^{(3)}}, P(Z_{t+1}^{(3)}|Z_t^{(3)}), P(X_t|Z_t^{(3)}))$ used for model detection and state estimation are:

Evening Model 1/PM1 (λ_1): This model is derived from the activity sequence $A^{(1)}{=}$ *hygiene, dress, cook, dine, clean, rest,* and *sleep*.

Evening Model 2/PM2 (λ_2): This model is derived from the activity sequence $A^{(2)}{=}$ *hygiene, dress, leave, hygiene, dress,* and *sleep*. We differentiate repeated activities as separate states with different self-looping state probabilities and characteristics. For example *hygiene* following the state *leave* may be longer in duration than *hygiene* upon arrival.

Evening Model 3/PM3 (λ_3): This model is derived from the activity sequence $A^{(3)}{=}$ *hygiene, dress, workout, cook, dine, clean, hygiene, dress, rest,* and *sleep*.

To benchmark performance, reference model λ_1 is used to generate 100 sample functions, or aggregate consumption sequences over $1{\leq}k{\leq}150$ time trials. We keep track of the hidden joint state $Z_t{=}A_t, C_t, E_t, F_t$, as well as the visible consumption emitted by the chain, $X_t{=}C_t{+}E_t{+}F_t$. For each sequence, we use a random function to generate a request R_t as a function of activity $P(R_t|A_t)$. For this study we set the grid alert consumption constraint to $z = 5$kW and examine the effects of the consumer parameter by analyzing system performance for $0{\leq}q{\leq}1$.

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TABLE II: Activities and dependent short-term appliances with associated wattage.

Activity	Dependent Devices	Range (W)
leave	alarm, lights	$0-1000$
hygiene	electric water heater, hairdryer, lights	$0-5000$
dine	toaster, microwave, lights	$0-3700$
rest	tv, lights	$0-650$
workout	treadmill, tv, lights	$0-2650$
dress	iron, lights	$0-1600$
clean	electric water heater, vacuum, lights	$0-4000$
sleep	alarm, lights	$0-1000$
cook	toaster, stove, coffeemaker, microwave, lights	$0-7500$

TABLE III: Long-term appliances, taxonomy, and associated wattage.

Appliance	"Shiftable"	Range (W)
electric vehicle supply (EVSE)	yes	$0-12000$
heating and air conditioning (HVAC)	yes	$0-40000$
dishwasher	yes	$0-1500$
refrigerator	no	$0-400$

A. Model Detection Performance

Using reference models λ_1, λ_2, and λ_3 to seed and generate three sets of 100 sample functions, we test the performance of the forward algorithm in detecting the best fit model. As described in section V, we evaluate the $\alpha_k(s)$ statistics along all states with respect to the model parameters of λ_1,λ_2, and λ_3 for a single sample function. We then calculate the sum, $\sum_{s\in\mathcal{S}_Z^\lambda} \alpha_k(s)$, along all states for each model and for each time trial in the sample function. We compare the value amongst all models considered. The model that results in the maximum value of $\sum_{s\in\mathcal{S}_Z^\lambda} \alpha_k(s)$ is the "best fit model" for that particular time trial. We repeat this process for all 100 samples generated by an individual seed model to validate the accuracy of the model detection algorithm. To produce figure 3 for each time trial in a single sample function we calculate the detection frequency of each model and repeat the process for the set of 100 sample functions seeded by the model parameters under consideration.

We are interested in studying the rate of convergence of correct model detection for each seed model which differ relative to one another based on the sequence and duration of behavioral activities. For example, evening model 2, or λ_2, is detected with a confidence exceeding 90% by the first time trial. This is due to the fact that the user *leaves*, which is an activity unique to λ_2 relative to λ_1 or λ_3. Furthermore, this particular model has a load characteristic influenced by the electric vehicle supply equipment (EVSE) fast-charging operation mode, followed by a period of little consumption during the activity *leave*. As shown in table III, λ_1 is detected with over 90% confidence by the 8th discrete time trial corresponding to 40 minutes. λ_3 is detected with over 90% confidence by the 10th discrete time trial corresponding to 50 minutes into the activity sequence. The rate of convergence between λ_1 and λ_3 may be due to structural similarities between models as well as activity sequences that have comparable consumption profiles. Thus, to achieve model detection within 90% confidence requires longer training periods depending on the model similarity.

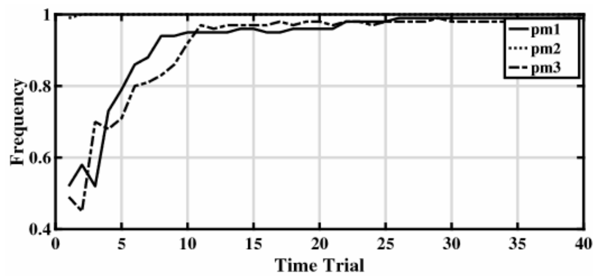

Fig. 3: Probability of detecting correct model for respective self-seeded sample functions.

TABLE IV: Model Detection: Time to 90% Confidence Levels

Evening Model	Interpolated Time Trial	Minutes
λ_1 (PM1)	7.3332	36.6660
λ_2 (PM2)	1	5
λ_3 (PM3)	9.6660	48.3300

B. Activity Influence on Consumption

To demonstrate the influence of human behavioral activity on load profile we examine the total consumption for the inventory of short-term and long-term appliances presented in tables II and III for individual human activities. For sake of clarity we present the expected consumption of two behavioral activities which can easily be extended to many. Figure 4 shows the expected consumption for the activities *cook* and *rest* for a time horizon of 5 trials corresponding to 25 minutes following the detection of the current wattage observation at time trial $t = 0$. The expected value for each activity is calculated by taking advantage of the hierarchical structure of each individual activity in terms of the activity dependent short-term devices and the activity dependent and independent long-term devices. We then examine the individual activity Markov chains which are homogeneous and discrete in state space allowing us to take advantage of the Chapman-Kolmogorov equations expressed as matrix multiplications describing the distribution of moving from the state at $t = 0$ to other states. Knowing the distribution allows us to calculate the expected consumption value by weighting the distribution with the discrete wattage value of each state, thereby obtaining the mean consumption at each time trial in the horizon considered. Note at time trial $t = 0$, the activities *cook* and *rest* both produce a total consumption observation of 41.4 kW. However, after time $t = 0$, *cook* and *rest* result in very different expected consumption observations. This is because *cook*, while producing a wattage observation of 41.4 kW, contributes to larger consumption observations due to additional appliance dependencies that *rest* does not include as illustrated in table II. Since the expected consumption is a function of the matrix multiplication form of the Chapman-Kolmogorov equations, with time the distribution decreases and reaches the stationary distribution for each individual activity.

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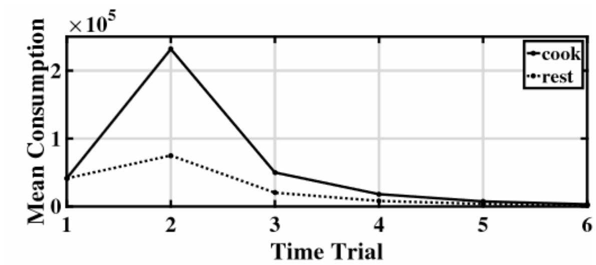

Fig. 4: Expected consumption over a time horizon of 5 trials for activities 'cook' and 'rest.'

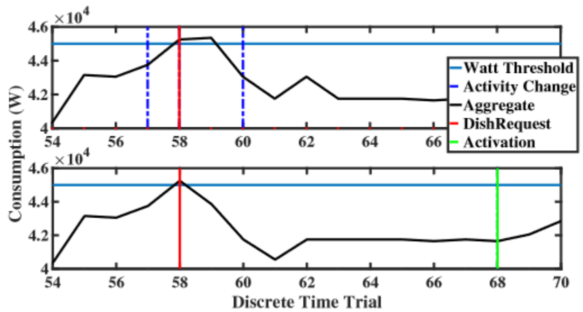

Fig. 5: Dishwasher scheduling comparison of visible Markov chain with detected model and estimated state.

C. Activity-Informed Control

We study the resulting scheduling control of the EMS for a sample function seeded by λ_1 as outlined in the procedure. Figure 5 presents a single sample function selected from the set of 100 simulations seeded by the model parameters of λ_1, also known as PM1. We select this particular sample to demonstrate the robustness of our control framework with respect to aggregate consumption and appliance scheduling despite inaccuracies in activity detection. In figure 5, we illustrate a case where the user prioritizes consumption constraints over appliance activation resulting in activation delay. The consumption constraint, labeled as "watt threshold," is representative of a pricing threshold via tiered pricing programs set by the utility. For example, the watt threshold may indicate a pricing shift from baseline to medium or peak consumption allowance. The cost savings would then be directly proportional to the reduction of time spent above the pricing defined consumption threshold. The first subplot of figure 5 shows the evening behavior of the user without the proposed energy management system (EMS). At the $t = 58$ time trial following behavior model detection outlined in section V, the user requests dishwasher activation. Since there is no EMS in place the dishwasher is activated upon request resulting in a load profile exceeding the consumption threshold from $t = 57.83$ to $t = 59.14$. This threshold is indicative of a specific tiered pricing program.Since tiered utility pricing programs vary with respect to location and region, we generalize our simulations to a consumption threshold which can be adapted to pricing depending on the utility provider. In the case of dynamic or time of use pricing, the consumption threshold represented as a constant would be replaced by a function specific to market demand or utility pricing respectively. In the second subplot of figure 5, the identical activity influenced load profile featured in the first subplot is considered under the control of the EMS wherein we demonstrate control over the single appliance *dishwasher*. The user similarly requests activation of the dishwasher at $t = 58$ time trial. In this subplot, the consumption threshold is exceeded from $t = 57.83$ to $t = 58.18$. However, we notice that the time spent above threshold is less than in the case without the EMS. In other words, irrespective of the scheduling request to activate the dishwasher, at time trial $t = 58$, the system was headed in an aggregate consumption condition in excess of the the consumption threshold set at 45kW. Following the request at $t = 58$, the EMS takes into account the probability of exceeding the consumption threshold level for the next 5 time trials and waits until the probability is low. In the fully visible Markov chain in the first subplot of figure 5, the household consumption, including the tagged changes in behavior at time trial $t = 57$ and time trial $t = 60$ are provided. In the hidden Markov chain, both of these human behavior activity transitions are not detected. In figure 6 we observe the likelihood of a particular human behavioral activity at each given point in time. At $t = 57$, there is a 0.7288 probability of the activity being *cook* following $t = 56$ where *cook* was detected with a high probability of 0.9948. At $t = 57$, there is a .2532 probability of the current activity being *dine* and an even smaller probability of 0.018 of the current activity being *clean*. Therefore, at $t = 57$ the maximum likelihood estimate of human behavioral activity is determined to be *clean* which remains unchanged from the detected behavioral activity of the previous time trial. Furthermore, at time trial $t = 60$, the maximum likelihood estimate determines *cook* to once again be the current activity with a probability of 0.7356 in contrast to the 0.2017 probability of *rest* and the 0.06097 probability of *dine*. Once again the results reflect that the framework makes reasonable estimates on the current activity based on aggregate consumption characteristics using the maximum likelihood despite some inaccuracies in detecting changes between states that may display similar load profiles. However, in later time trials beyond $t = 66$ we see the activity *rest* increasing in probability which illustrates that though the HMM framework may not detect behavioral activity at a high resolution, after some time and updated observations, the correct behavioral activity will be detected with some delay which influences the scheduling EMS control system.

The goal of the study is to utilize human behavior schedules to infer demand for a rolling time horizon in order to schedule appliances under consumption constraints defined by utility pricing and consumer preferences. In the case where consumption thresholds are prioritized over consumer comfort with respect to appliance activation delay, the control mechanism schedules the dishwasher to run at time trial $t = 68$, 50 minutes following dishwasher appliance activation request. Figure 5 shows the scheduling and the resulting aggregate power consumption following dishwasher activation at a time of low load demand.

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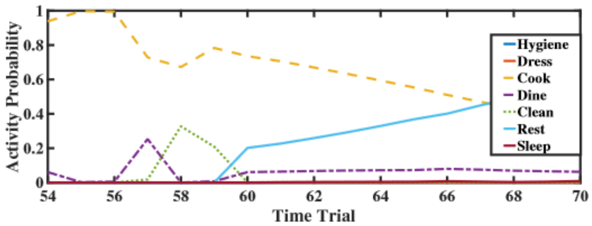

Fig. 6: Single sample function activity probability.

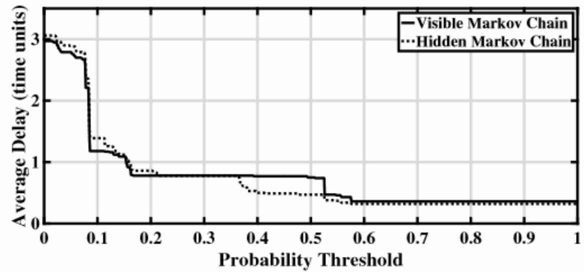

Fig. 7: Appliance activation delay as a function of q.

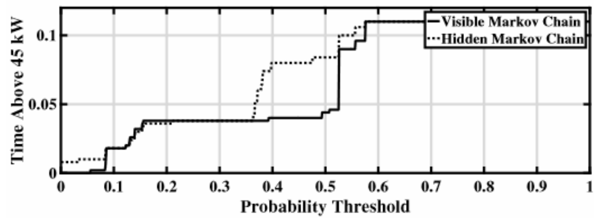

Fig. 8: Average time above $X_t \geq 45$kW.

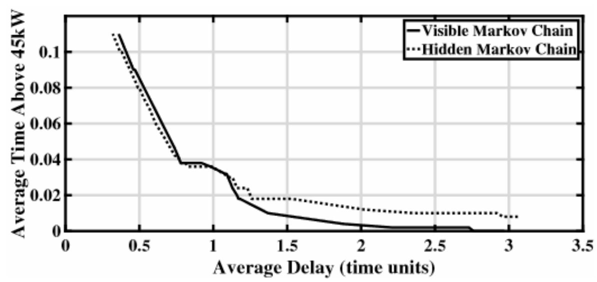

Fig. 9: Average time above $X_t \geq 45$kW as a function of delay.

D. Comfort Consumption Tradeoff

We present the results of a simulation study that takes into account the consumer comfort level in terms of the activation delay with respect to appliance requested as well as the consumption threshold constraint. This study differs from previous work in that the activity informs the future consumption values for a time horizon that is dependent on the operational cycle of the appliance being controlled. In this study we continue to study the control of the dishwasher in terms of the delay in appliance activation given consumer comfort and the expected time in units of time trials, where each time trial represents 5 minutes, of the aggregate consumption exceeding the consumption threshold of 45kW. From figure 7 we examine the delay in appliance activation as a function of the consumer comfort parameter we have generalized as "probability threshold." In these results, taken over 100 sample functions for 1001 probability thresholds ranging from $0-1$ in uniform increments we compare and contrast the performance results of the fully visible Markov chain with the hidden Markov chain detected by the EMS framework. We see that the relationship occurs in discrete steps which is the result of the discrete construction of the chain and an effect of its Bakis characteristics. However, we see that the hidden Markov chain performs relatively well with respect to the fully visible chain but degrades for probability "comfort" values between 0.363 to 0.576 indicating premature activation of the appliance. To examine how the premature activation of the appliance affects the consumption threshold constraint we plot the mean time above the consumption threshold of 45 kW with respect to the probability threshold and again examine the results obtained for probability "comfort" values within this range. In figure 8 we notice within the window of "comfort" probability thresholds from 0.363 to 0.576, the EMS early activation, unsurprisingly results in larger times above 45kW consumption threshold. This is due to the fact that the HMM framework has less information that the fully visible chain resulting in some degree of error that may be inherent to the simulation. In real systems, increased sample data with respect to consumption and behavioral activity on a daily basis offers some alleviation. The tradeoff between the average discrete time spent above consumption threshold as a function of delay is presented in 9. We see that the time spent above the 45kW is inversely proportional to the average activation delay calculated across the "comfort" probability constrained sample functions. In other words, the "comfort" probability allows a degree of freedom for the consumer in terms of choosing device activation irrespective of the consumption threshold set by the EMS.

VIII. Future Work

Future work in this project can take many interesting directions. In the paper presented, we considered the control and appliance scheduling for the dishwasher. In reality, different heavy consumption long-term appliances may be considered in other case studies. For example, the HVAC, which we have included in our case study as a long-term activity dependent appliance, represents a major load that has been the target of discretionary utility programs within current demand response. In the study presented, we did not seek to control this particular appliance due to dependencies with respect to the external temperature and weather, but we did include it as an influential contribution to the aggregate load. Additionally, our residence case simulation study presented the EVSE as a load that is used simply to charge the car with a dependency on consumer occupancy via the detection of the activity *leave*. We did not consider using the car battery or an external battery as a distributed energy resource (DER) in our scheduling framework to offset peaks. Future work seeks to build upon this

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study with the inclusion of energy resources such as energy storage systems and photovoltaic cells whose lifetimes depend on charge/discharge stress as well as cloud cover respectively. In addition to further appliance case studies, alternative EMS frameworks may also be considered using different mathematical models for activity detection and appliance scheduling. Unfortunately, frameworks based on Markov models suffer from the curse of dimensionality. In other words, the amount of states with respect to individual users, behaviors, and appliance states quickly becomes intractable impacting the optimization process used to implement system control. Recall, in Section VI-A, we calculate the probability of exceeding a power grid defined threshold over a finite horizon corresponding to the cycle duration of a long-term appliance. The complexity of this process in terms of the number of operations required for calculation grows with the number of states where each time slot requires $O(S \times S)$ operations [29]. Calculations are especially difficult when scaling the framework to a neighborhood or residential group level. Large state spaces correspond to lengthy estimation, slow convergence and high complexity of optimization. To scale up our model we must reduce the model or use alternative techniques. Alternatives such as graph signal processing approaches as presented in [30] may alleviate complexity issues. We leave a thorough evaluation of alternative techniques in the scenario described in this paper for future work. Finally incorporation of complementary work in non-intrusive load monitoring may inform better generalized appliance models. For example, [31] generalized appliance models from sub-metered appliance datasets of different makes and models of devices using supervised learning techniques followed by sampling to obtain averaged appliance instances depending on the appliance type. The general models were then used to disaggregate load curves from publicly available consumption datasets. While the goal of this project is to study human activity as a driver of consumption rather than load disaggregation, building a tagged dataset of consumption and behavior would provide a means of evaluating load disaggregation methods with an additional degree of freedom.

IX. Conclusions

In this paper we proposed an energy control framework driven by consumer behavior as an alternative to price driven systems. The EMS detected behavior according to pre-built reference models differing in activity sequence. Following model detection, the intelligent control agent assessed user appliance requests based the state estimate, a grid-informed consumption constraint, and a consumer convenience parameter. Results support that inclusion of human behavior as a driver for demand affects accurate consumption prediction which is necessary for EMS appliance scheduling. Consumer convenience constraints based on the current state estimate and the consumption constraint provided a means for the resident to control appliance activation delay. A case study demonstrated the effectiveness of the system as a whole.

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