Consumer in-the-Loop: Consumers as Part of Residential Smart Energy Systems

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***Abstract*— A novel framework for residential smart energy systems is proposed. The model integrates the consumer behavior in the dynamics of the technological and environmental components of the system. The objective is to classify and optimize the whole system, which includes the dynamics of the consumer. The framework is based on Markov process, model detection and Hidden Markov Model Theory. The behavior of the consumer is classified from a sequence of available observations within a set of reference classes. The detected class is used as prior information to detect the state of the system and provide feedback to the consumer to reduce the probability that undesirable states occur within a time window.**

I. Introduction

The electricity supply grid is an extremely complex machine, whose monitoring and control present inherent difficulties due to its large topology and to the distributed nature of some of its components. The Smart Grid [1], [2] evolves the traditional electricity grid to address the environmental challenges of the 21st century, and the structural shortcomings of the traditional approach to power distribution, such as reliability. To fulfill its mission, the Smart Grid revolutionizes the top-down approach of the traditional grid by introducing intelligence at all levels of the system, in addition to information technologies to connect them. In the Smart Grid, the edge of the system, the individual household, deeply integrates to the overall system management chain by actively reacting to grid signaling, and making energy consumption and scheduling decisions [3]. On the one hand, the Smart Grid inherits from the traditional grid, and further exacerbates, the large-scale challenges at the power distribution level [4]. On the other hand, the Smart Grid introduces a further level of complexity and challenge: *the design and optimization of the operations of the local controllers*.

At the local level, automation in smart buildings and the implementation of demand response systems has been a central topic in the development of the Smart Grid. A consistent body of work proposed and studied algorithms for the optimization of *energy tasks*' scheduling (*e.g.*, see [5]–[8]). Recently, there has been a rising interest in frameworks representing the dynamics of residential systems as Finite State Machines (FSM) with Markovian state transitions [9]–[14]. [1] The seminal work [9] presented a Markov model capturing simple dynamics of appliance activation and energy scheduling. A reinforcement learning algorithm was used to minimize the weighted sum of the average financial cost of operations and appliance activation delay. The popularity of frameworks based on a FSM/Markovian representation over other options comes from the inherent simplicity of the model, which captures key dependencies in the temporal evolution of the system, as well as interdependencies in the evolution (*e.g.*, activation, de-activation) of individual components. This representation also enables the use of a wide range of well studied analysis and optimization tools such as dynamic programming [16] and hidden Markov models [17].[2] Thus, while the design of grid-wide control rationale focuses on the physical topology identified by a graph where nodes are physical components (*e.g.*, power plants, loads) and the edges are power-lines, the design of management systems focuses on graphs modeling the fine-grain temporal evolution of local systems. In the latter case, nodes are logical states of the system, and edges are state transitions with non-zero probability. This perspective, first proposed in [11], opens to new analysis and design principles.

However, prior literature investigating FSM-based models for smart energy systems does not consider one of the central elements of the system's dynamics, which also is one of its largest unknown: the consumer. Work where the role of the consumer is heavily emphasized (*e.g.*, [18]) does not capture the dynamics of the consumer and their interaction with the technological components of the system. The model proposed herein incorporates in the multidimensional FSM modeling the overall system components tracking the current *activity* of the consumer (*e.g.*, dining, sleeping, watching television), as well as the fundamental features influencing the stochastic characterization of the system's dynamics. Besides improving the ability of automated demand response systems to generate scheduling while jointly minimizing the financial cost of operating devices and maximizing consumer comfort, we argue that this modeling rationale creates a new synergy between applications and fundamental tools. Based on this model, tools for the observation, classification and influence of the consumer dynamics can be developed. Thus, the consumer becomes part of the *observation-analysis-control loop* of the smart energy system, where feedback is actively proposed to the consumer to *steer* the trajectory of the system behavior. Prior work proposed the estimation of user's activities and tasks in smart home environments from sensors and energy usage measurements [19], [20] which can be used to build the reference models.

The rest of the paper is organized as follows. Section II

[1] See [15] for an overview of Markov process theory.

[2] Note that while these tools are often theoretically applicable to continuous state space and general distribution, the practical use is often limited to Markov processes with finite state spaces.

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describes the residential smart energy system and its components. Section III presents the FSM model with Markovian state transitions used in this paper. In Section IV, the classification, state detection and feedback framework is presented. Section V-A describes the case study models used to generate the numerical results presented in Section V-B. Section VI concludes the paper.

II. Smart Energy Systems

Residential smart energy systems are cyber-physical systems integrating a set of interacting heterogeneous sub-systems. The sub-systems are *environmental*, *technological* and *human*. The system can implement control and adaptation functionalities based on implicit or explicit, internal or exogenous information acquisition. In this section, we briefly sketch the individual sub-systems and discuss their mutual influence, as well as the objectives and challenges of the system management.

Consumer Component: The center of the smart energy system is the consumer, whose activity and needs determine the energy consumption and management of the household. The daily routine can be represented as a sequence of descriptors and activities that determine the activation of devices and appliances, battery charging, as well as specific environmental parameters to be maintained. The sequence of activities (*e.g.*, cooking, dining, sleeping) presents an intrinsic correlation. For instance, sleeping is likely to happen after dining, which typically occurs after cooking. Additionally, the sequence of activities is also influenced by descriptors such as the geographical location of the consumer. For instance, the initiation of the cooking (and then dining) activity may be highly correlated with the return home after work indicated by a change of the location descriptor. Each activity is characterized by a sub-sequence of activations of devices and appliances. Note that some devices may not be directly related with the activity. For instance, electric vehicles may be charging while the consumer is sleeping. The stochastic model presented in Section III captures the correlation in the consumer behavior and their interaction with the other sub-systems.

Technological Components: The consumer interacts with a number of technological sub-systems such as appliances, devices and the energy management system. The temporal evolution of these components is correlated with that of the consumer. By activating some appliances (*e.g.*, the dishwasher), the consumer triggers a *cycle* where each stage is characterized by a set of features such as remaining active time and consumption. The end of the cycle may trigger with high probability some evolution of the state of the consumer (*e.g.*, cookware is clean and cooking may be initiated). The active time of other appliances, such as lights and the stove, may be determined by the current consumer activity. Thus, *the strong correlation in the evolution of the different components of the smart energy system can be used to classify the consumer, detect their state and influence their daily routine*.

The interaction with the grid-wide system is more subtle. The aggregate of the local consumers and technological system activity can impact the stability of the grid and influence energy pricing and trigger demand response signaling which affect local activity. Alternatively, pricing and demand response signaling may influence the behavior of the consumer, or the scheduling generated by the automatic controller. Again, by integrating the activities of the consumer as part of the overall model, we capture these dynamics.

Environmental Components: Environmental variables such as weather conditions, external temperature, and internal temperature, have a significant influence on the dynamics of the smart energy system. For instance, the internal temperature, whose dynamics are function of the external weather and temperature, influences air conditioning activation to maintain the household within a comfort region. Additionally, there might be a degree of correlation between the external weather conditions and the activities of the consumer. Modeling this interaction can lead to more accurate local and global consumption predictions.

Energy Management System: The core of the residential smart energy system is the Energy Management System (EMS), which consists of a network of sensors, an information processing unit, and a control loop. The EMS may also be capable of connecting to communication networks to forward information to and receive information from the energy grid. Locally, based on the collected information, the EMS generates scheduling of appliances and devices activation aiming at reducing financial cost of operations, maintaining consumer comfort and satisfaction, and complying with grid-wide objectives. We argue that the consumer is not only one of the main driving components for the behavior of the system, but is an integral part of the smart energy system when analyzing and optimizing the dynamics as a whole. By explicitly introducing activity of the consumer in the model, we enable a variety of applications aimed at improving the overall efficiency by influencing the consumer dynamics. Herein, we focus on the classification of the consumer, on the estimation of their instantaneous state, and on the construction of feedback signals aimed at avoiding undesirable system's conditions. The integration of the above applications with energy scheduling is left for future research.

III. Stochastic Model

We model the temporal evolution of the system as a Markov process with a finite state space [15]. As a first approximation, we assume that the Markov process is homogeneous. However, changes over time of the statistics can be included both in the model and in the analysis tools. For the sake of simplicity, we consider time slots of duration Δ, where the slots are indexed with $t{=}0, 1, \ldots$.

From the standpoint of stochastic modeling, the individual components correspond to sub-chains, whose temporal evolution is mutually interdependent. The overall state $s{=}\{x_n\}_{n=1,\ldots,N}{\in}\mathcal{S}$, where $\mathcal{S}$ is the state space of the system, $\{x_n\}_{n=1,\ldots,N}$ describes the state of the individual sub-chains, and N is the number of sub-chains. The Markov process is the sequence $(S(0), S(1), S(2), \ldots)$, where $S(t){=}\{X_n(t)\}_{n=1,\ldots,N}$ is the state at time t.[3] The statistics of

[3] We use "at time t" and "in slot t" interchangeably.

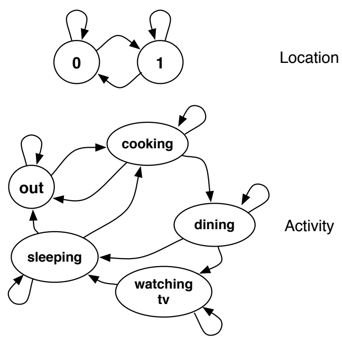

Fig. 1. Sub-chains modeling the presence of the consumer in the house and their current activity.

the system are fully defined by the transition probabilities

$$p(s''|s') = P(S(t+1){=}s''|S(t){=}s'), \quad (1)$$

$\forall t{=}0, 1, \ldots, \forall s', s''{\in}\mathcal{S}$, and $p_0(s_0){=}P(S(0){=}s_0)$, where $P(\cdot)$ denotes the probability of an event. We assume that the process has one recurrent class and that the chain is aperiodic [21]. These assumptions guarantee the existence of a proper steady-state distribution $\pi(s)$, $s{\in}\mathcal{S}$. The transition probability matrix and the vector collecting the steady-state distribution are denoted with $\mathbf{P}$ and $\boldsymbol{\pi}$, respectively.

A. Components

First, we describe the individual sub-chains. We remark that the temporal evolution of the sub-chain is coupled, that is, while the temporal evolution of the overall system is assumed Markovian, the trajectory of an isolated sub-chain is not. Thus, the overall transition probabilities cannot be factored based on the marginal transition probabilities of the individual chains. However, the logical division of the overall chains into *dimensions* or sub-chains provides a good intuition of the system's dynamics.

Consumer Descriptors: The core of the model are the sub-chains that determine the temporal evolution of consumer descriptors and activities. The physical location of the consumer is one of the most influential descriptors in the overall model. The state space can be constructed to indicate the presence in the house of the consumer (see Fig. 1), or to capture the position within the house, as well as to include other relevant locations such as the workplace. The transitions probabilities determine the sequence of and the permanence time in the location states. We remark that the transition probabilities are influenced by the state of the other sub-chains to capture the interactions between the components of the system. For instance, the transition probabilities of the consumer sub-chain may be function of the activation/deactivation of specific appliances, which is captured by state transitions of other sub-chains.

The current activity is a sub-chain whose states are associated with logical descriptor of the consumer state. The example depicted in Fig. 1 includes activities such as sleeping, dining, cooking. watching TV (a methodology to build a set of activities can be found in [19], [20]). The state space of this sub-chain distinguishes between all the activities that are

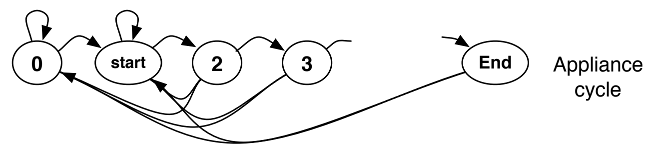

Fig. 2. Sub-chain modeling the cycle of an appliance.

relevant to correctly track a sequence of events and capture correlation with other sub-chains. For instance, *cooking* may capture the correlation with the activation of some appliances (*e.g.*, the stove), but may fail to provide a good model for the sequence of the activities. For instance, by distinguishing cooking performed at different time of the day (breakfast, lunch, dinner), the activity sub-chain provides meaningful transitions to following activities such as dining, going out to work or watching TV. That is, cooking clusters activities that are associated with the same set of appliances, but that need to be separated to provide a meaningful daily routine. Analogous activities may also be divided to capture different duration distributions.

Appliances and devices: The sub-chains associated with the appliances and devices capture activation/deactivation and the evolution over time once activated. Some appliances such as lights, are associated with on/off sub-chains whose transitions are determined by the activity. Some appliances present a non-binary state space to capture their cycle, where every state corresponds to a stage (see Fig. 2). For instance, the state of an active dishwasher deterministically moves through a sequence of states characterized by a specific energy consumption. We observe that additional states can be added to obtain an accurate model of complex activation patterns. For instance, a sub-chain tracking the internal temperature of the refrigerator can be added to model inter-activation intervals. Additional states can also be used to prevent early re-activation of an appliance. For instance, once the dishwasher cycle is terminated, it is unlikely that the appliance is activated before the activity sub-chain hits again the subset of states corresponding to cooking, and a state can be added to the cycle to prevent re-activation.

Environment: Sub-chains can be defined whose state space includes descriptors of external parameters such as the temperature and solar radiation. The states are obtained by quantizing continuous variables, and, thus, their temporal evolution is approximated as a trajectory on a finite state space. However, the applications proposed in this paper require a manageable model providing an acceptable degree of accuracy, rather than an extremely accurate model whose analysis and optimization is excessively complex. The trajectory of the environmental variables influences the transition probabilities of the consumer sub-chains, as well as the activation of devices in the house.

B. Observations

The trajectory of the FSM generates a sequence of observations available at the EMS. Observations are acquired via a generalized network of sensors, which may include heterogeneous devices such as the smart meter (overall consumption), the smart phone (GPS location), internal sensors (room occupancy) and smart appliances (on/off and cycle of individual appliances). Thus, the EMS observes the state of a subset of sub-chains, and functions of the state such as the aggregate consumption generated by the active appliances.

We define the observation space $\mathcal{O}$ and the observation map $\omega(o,s) = P(O(t){=}o|S(t){=}s)$, $\forall s{\in}\mathcal{S}, o{\in}\mathcal{O}$. Thus, the function ω is a distribution on the observation space conditioned on the state of the system. Note that the state-observation process $\{S(t), O(t)\}_{t=0,1,\ldots}$ is a Markov process, while the observation sequence is not Markovian.

C. Classification, Undesirable States and Feedback

Based on the FSM model with Markovian transitions described above, we design an algorithm that classifies the behavior of the consumer and their interaction with the other components of the system. The behavior of the consumer and their influence of the activation of devices and appliances is determined by the Markov process $\mathcal{M}{=}(\mathcal{S}, \mathbf{P}, \boldsymbol{\pi}, \omega)$. Each class, thus, corresponds to a reference model $\mathcal{M}_c{=}(\mathcal{S}, \mathbf{P}_c, \boldsymbol{\pi}_c, \omega)$, $c{=}1,\ldots,C$, where C is the number of classes.[4] Our classification problem, then, amounts to the identification of the model $\mathcal{M}^*{\in}\{\mathcal{M}_c\}_{c=1,\ldots,C}$ which is most likely generating the sequence of observations $\mathbf{o}{=}(o_0, o_1, o_2, \ldots)$. As explained in the following, the quantities necessary to detect the consumer model, can be also used to estimate the most likely trajectory of the consumer state. Additionally, once the model is estimated, we design a state estimation and feedback system that alerts the consumer if undesirable system's state are likely to occur in the near future. We define the set of undesirable states $\mathcal{U}{\in}\mathcal{S}$, the time window $W{\in}1,2,\ldots$ and the threshold $\phi_{\max}{\in}[0,1]$. Feedback is generated if the probability that the set $\mathcal{U}$ is reached in W slots from the estimated state is larger than $\phi_{\max}$.

IV. Consumer Classification, State Detection and Feedback

Most of the current work on residential smart systems using dynamical models focuses on the scheduling of energy tasks. The integration of the consumer as a central component of the residential smart energy system enables a variety of applications. Herein, we focus on consumer behavior classification, consumer state prediction, and feedback to the consumer.

A. Consumer Classification

We denote the sequences $(o_{t_1}, o_{t_1+1}, \ldots, o_{t_2})$ and $(s_{t_1}, s_{t_1+1}, \ldots, s_{t_2})$ as $\mathbf{o}_{t_1:t_2}$ and $\mathbf{s}_{t_1:t_2}$, respectively.

The probability that the consumer class is $\mathcal{M}_c$ conditioned on the observation sequence $\mathbf{o}_{0:T}$ is

$$P(\mathcal{M}_c|\mathbf{o}_{0:T}) = P(\mathbf{o}_{0:T}|\mathcal{M}_c)P(\mathcal{M}_c)/P(\mathbf{o}_{0:T}). \tag{2}$$

[4]Note that it is assumed that all the models have identical state spaces and state observation map.

Thus, assuming all the classes have the same prior probability $P(\mathcal{M}_c)$, the estimated model is

$$\mathcal{M}^* = \arg\max_c P(\mathcal{M}_c|\mathbf{o}_{0:T}) = \arg\max_c P(\mathbf{o}_{0:T}|\mathcal{M}_c). \tag{3}$$

The probability of the observation sequence conditioned on the class $P(\mathbf{o}_{0:T}|\mathcal{M}_c)$ can be computed as shown in Eq. (4), where $\mathbf{S}_T$ is the space of the state sequences of length $T{+}1$. We use the *forward-backward procedure* [22] to compute the model and state distribution conditioned on the sequence of observations. First, define $\alpha_t^c(s)$, $t{=}0,\ldots,Q$ and $\forall s{\in}\mathcal{S}$, recursively as $\alpha_0^c(s){=}\pi_c(s)\omega(s,o_0)$ and

$$\alpha_t^c(s') = \sum_{s\in\mathcal{S}} \alpha_{t-1}(s)p_c(s'|s)\omega(s',o_t),\ t{>}0. \tag{5}$$

Note that $\alpha_t^c(s'){=}P(\mathbf{o}_{0:t}, S(t)=s'|\mathcal{M}_c)$, therefore

$$P(\mathbf{o}_{0:t}|\mathcal{M}_c) = \sum_{s'\in\mathcal{S}} \alpha_t^c(s'). \tag{6}$$

Then, the class estimate in slot t based on the current sequence $\mathbf{o}_{0:T}$ is

$$\mathcal{M}_t^* = \arg\max_c \sum_{s'\in\mathcal{S}} \alpha_t^c(s'). \tag{7}$$

B. State Identification and Feedback to the Consumer

Once the model is estimated based on a training period, the full observed sequence can be used to retrieve the state trajectory. We, then, define $\beta_t^c(s)$, $t{=}0,\ldots,T$ and $\forall s{\in}\mathcal{S}$, as $\beta_T^c(s){=}1$ and

$$\beta_t^c(s) = \sum_{s'\in\mathcal{S}} \beta_{t+1}(s')p_c(s|s')\omega(s',o_{t+1}). \tag{8}$$

Note that $\beta_s^c(t){=}P(\mathbf{o}_{t+1:T}|S(t){=}s,\mathcal{M}_c)$. Then, the estimate of the state at time t conditioned on the class estimate is $s_t^* = \arg\max_{s\in\mathcal{S}} \gamma_t(s)$, where

$$\gamma_t(s) = \alpha_t^*(s)\beta_t^*(s) / \sum_{s'\in\mathcal{S}} \alpha_t^*(s')\beta_t^*(s'). \tag{9}$$

Note that in the online version of the above estimation, the state to be estimated is the last in the observation sequence is s_T. As $\beta_T^*(s){=}1$, $\forall s{\in}\mathcal{S}$, then only the backward values are used, that is, only the past history is used to estimate the current state.

Based on the state and model estimate, we compute the probability $\phi^W(s_t^*,\mathcal{U})$ that the process hits the set of undesirable states $\mathcal{U}{\subset}\mathcal{S}$ from a state s within W slots. Define $\tau_s(\mathcal{U})$ as the first hitting time of the set $\mathcal{U}$ from state s, that is,

$$\tau_s(\mathcal{U}){=}\min\{t' : S(t{+}t'){\in}\mathcal{U} \mid S(t){=}s\}. \tag{10}$$

Thus, we have that

$$\phi^W(s,\mathcal{U}) = P(\tau_s(\mathcal{U}){\le}w) = \sum_{w=1}^{W} P(\tau_s(\mathcal{U}){=}w). \tag{11}$$

$$P(\mathbf{o}_{0:T}|\mathcal{M}_c){=}\sum_{\mathbf{s}_{0:T}\in\mathbf{S}_T} \pi_c(s_0)\omega(s_0,o_0) \prod_{q=1,\ldots,T} p_c(s_t|s_{t-1})\omega(s_q,o_q), \tag{4}$$

In order to efficiently compute the distribution $P(\tau_s(\mathcal{U}){=}w)$, $w{=}1,\ldots,W$, we define the *taboo* probability [21]

$$_{\mathcal{A}}P^w(\mathcal{B}|s) = P(S(t{+}w){\in}\mathcal{B} \mid S(t){=}s, \tau_s(\mathcal{A}){\geq}w). \quad (12)$$

The taboo probabilities admit the recursive computation

$$_{\mathcal{A}}P^w(s|\mathcal{B}){=}\sum_{s'\in\mathcal{A}^c} p(s'|s)\,_{\mathcal{A}}P^{w-1}(\mathcal{B}|s') \quad (13)$$

where $\mathcal{A},\mathcal{B} \subseteq \mathcal{U}$, and where $\mathcal{A}^c = \mathcal{S}\backslash\mathcal{A}$, and where $_{\mathcal{A}}P^1(s|\mathcal{B}){=}\sum_{s'\in\mathcal{B}} p(s'|s)$. Then, the probability $P(\tau_s(\mathcal{U}){=}w)$ is equal to $_{\mathcal{U}}P^w(s|\mathcal{U})$. Note that the probability that the undesirable state region is hit by the process can be computed over the state distribution $\gamma_t(s)$ at the price of an increased complexity.

An alert to the consumer is issued if $\phi^W(s,\mathcal{U}){\geq}\phi_{\max}$. A recommendation on the actions to avoid/implement in the time window can be formulated by analyzing the events present in the sequences leading to the set $\mathcal{U}$. Due to space constraints, we refer the interested reader to future publications for a complete discussion on the analysis of W-slot sequences for action-specific recommendations.

As a final remark, we observe that a possibly significant reduction in the computational complexity of classification, state estimation and feedback can be obtained by considering only recurrent states [21]. In fact, after a sufficient amount of time, which depends on the mixing time of the Markov chain, the trajectory of the system is confined to a single recurrent class, and transient states can be pruned from the state space, stationary distribution and transition probability matrix.

V. Numerical Results

In this section, we present results illustrating the proposed model and assess the performance of the classification and estimation algorithms. We focus on the case study described below.

A. Case Study

We remark that the models used herein are case study models used to illustrate the proposed modeling and classification/feedback technique. The construction of models from real data is left for future studies. We consider two consumer classes (class 1 and class 2), where one time slot corresponds to 15 minutes. A binary variable tracks the location of the consumer, where $L(t){=}1$ and $L(t){=}0$ correspond to consumer present and not present in the household. The activities included in the model are: none $A(t){=}0$, sleeping $A(t){=}1$, cooking breakfast $A(t){=}2$, cooking dinner $A(t){=}3$, dining $A(t){=}4$ and watching television $A(t){=}5$. The appliances included are the electrical stove, the lights, the television and the dishwasher. Note that while stove, lights and television can be modeled as binary on/off sub-chains whose transitions are fully dictated by the consumer, the dishwasher cycle has a temporal evolution independent of the consumer activity as discussed in Section III. The observed variable is the overall quantized instantaneous power consumption $O(t){\in}\{0,1,2,\ldots,10\}$. The undesirable states are those associated with a consumption larger than a threshold ψ.

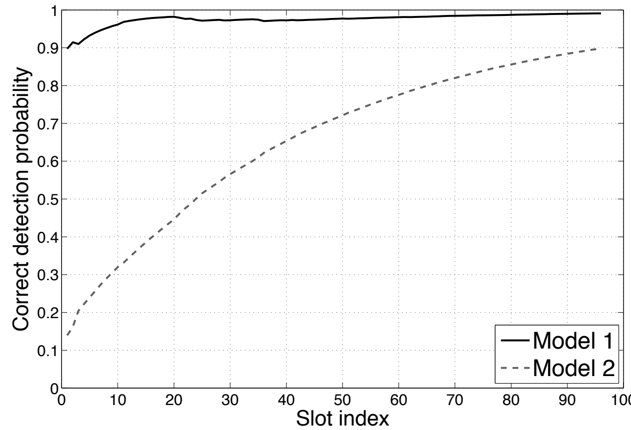

Fig. 3. Probability that the correct model is detected as a function of the slot.

Class 1: The daily routine of the consumer consists of a sequence of activities that starts with cooking breakfast followed by a period out of the house for work. Once the consumer returns home, the consumer cooks dinner, dines and then either sleeps or watches TV before the sleeping period. We remark that the permanence time in each location/activity is a random variable. We set the transition probabilities so that the permanence time at work is 8 hours on average, and the permanence time in the sleeping, cooking breakfast, cooking dinner, dining and watching TV is 8 hours, 20 mins, 1 hour, 1 hour and 2 hours, respectively. The probability that the consumer watches TV before going to sleep is 0.9.

Class 2: Differs from class 1 with respect to the lack of a dishwasher as an appliance, and the fact that the schedule proceeds as follows: the consumer cooks breakfast, leaves for work, returns to have lunch, leaves for work, returns to cook and dine, then proceeds to either sleep or watch television. The duration of the periods in which the consumer "works" is set to 4 hours. The permanence in each state is identical to class 1 with the exception of the 7 hours 30 mins sleeping state and an additional 30 mins lunch state. The probability that the consumer watches TV before going to sleep is 0.9.

B. Performance

Fig. 3 shows the probability that the correct model is detected as a function of the slot, that is $P(s^*(t){=}s_t)$. The probability is computed over 400000 state sequences of 96 slots (1 day) randomly generated according to each model. It can be observed that at the end of a 1 day sequence, the consumer is correctly classified in more than 90% of the sequences in both models. However, whereas the classification of sequences generated by model 1 is accurate even if a small number of observations is available, an accurate classification of sequences generated by model 2 requires a larger number of observations. This is due to the non-zero probability that model 1 generates high consumption observations (*e.g.*, simultaneous activation of dishwasher, stove and lights). On the other hand, to correctly classify sequences generated by model 2 the detector needs to compare the distribution of the observations. The detection of the consumer class within a larger set of

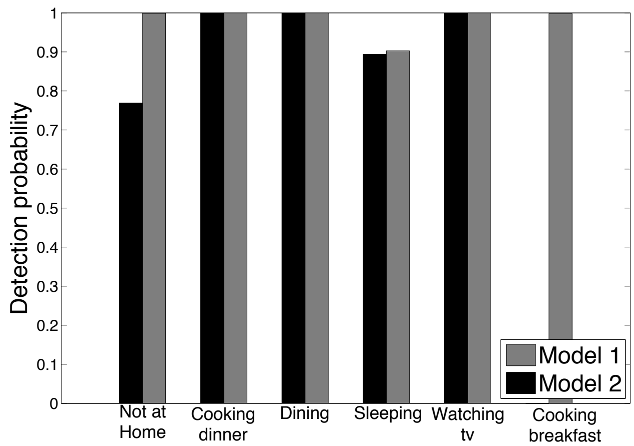

Fig. 4. Probability that the correct consumer state is correctly detected.

classes may require longer sequences of observations. However, the preliminary results presented herein indicate that the time needed to detect the consumer class within a reasonable number may be of the order of days.

Fig. 4 shows the probability that the consumer state is correctly estimated assuming the model is correctly classified. If the consumer belongs to class 1, then the only state with a non-negligible probability of misdetection is *sleeping*. In fact, *sleeping* and *not at home* generate the same consumption observation. *In most cases the detector is capable of distinguishing between the two states due to correlation in the sequence of consumer states. Therefore, including the dynamics of the consumer in the model brings a clear advantage in detecting and predicting the consumer state.* If the consumer belongs to class 2, then the two states (*sleeping* and *not at home*) are exchanged in a larger fraction of cases due to the more involved dynamics of the consumer. We remark that the model and state detection accuracy can be improved by acquiring richer observations. For instance, location information can be collected via the GPS installed in the smart phone, and smart appliances may feedback activation information to the detector.

In all analyzed sequences the feedback signal is correctly generated to the consumer. Thus, even if states are misdetected with some probabilities, states where the alert signal is active are never detected as states where the alert signal is not active and vice versa.

VI. Conclusions

A novel framework for classification, state estimation and feedback in smart energy systems was proposed. The framework emphasized the central role of the dynamics of the consumer and their interaction with the technological and environmental components. The temporal evolution of the overall system was modeled as a FSM with Markovian transitions. By including consumer activity as an integral part of the model, the proposed framework opens up to novel approaches for classification, estimation, and consumer dynamics. Preliminary numerical results assess the performance of classification and feedback generation for a case study proposing two models for the dynamics of the smart energy system.

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