Context-Aware Resource Management in Multi-Inhabitant Smart Homes: A Nash H-Learning based Approach *

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Abstract

A smart home aims at building intelligence automation with a goal to provide its inhabitants with maximum possible comfort, minimize the resource consumption and thus overall cost of maintaining the home. 'Context Awareness' is perhaps the most salient feature of such an intelligent environment. Clearly, an inhabitant's mobility and activities play a significant role in defining his contexts in and around the home. Although there exists an optimal algorithm for location and activity tracking of a single inhabitant, the correlation and dependence between multiple inhabitants' contexts within the same environment make the location and activity tracking more challenging. In this paper, we first prove that the optimal location prediction across multiple inhabitants in smart homes is an NP-hard problem. Next, to capture the correlation and interactions of different inhabitants' movements (and hence activities), we develop a novel framework based on a game theoretic, Nash H-learning approach that attempts to minimize the joint location uncertainty. The framework achieves a Nash equilibrium such that no inhabitant is given preference over others. This results in more accurate prediction of contexts and better adaptive control of automated devices, leading to a mobility-aware resource (say, energy) management scheme in multi-inhabitant smart homes. Experimental results demonstrate that the proposed framework is capable of adaptively controlling a smart environment, thus reducing energy consumption and enhancing the comfort of the inhabitants.

1 Introduction

Advances in smart devices, mobile wireless communications, sensor networks, pervasive computing, machine learning, middleware and agent technologies, and human computer interfaces have made the dream of smart environments a reality. According to [2], a "smart environment" is one that is able to autonomously acquire and apply knowledge about its inhabitants and their surroundings, and adapt to the inhabitants' behavior or preferences with the ultimate goal to improve their experience. The type of experience that individuals expect from an environment varies with the individual and the type of environment considered. This may include the safety of inhabitants, reduction of cost of maintaining the environment, optimization of resources (e.g., energy bills or communication bandwidth), or task automation. An instance of such an indoor environment is a *smart home* that perceives the surroundings through sensors and acts on it with the help of actuators.

An important characteristic of such an intelligent, ubiquitous computing and communication paradigm lies in the autonomous and pro-active interaction of smart devices used for tracking inhabitants' important contexts such as current and near-future locations as well as activities. *Context awareness* is indeed a key to build a smart environment and associated applications. As for example, the embedded pressure sensors in the Aware Home [13] capture inhabitants' footfalls, and the system (i.e., smart home) uses these data for position tracking and pedestrian recognition. The Neural Network House [12], the Intelligent Home [11], the Intelligent House_n [8] and the MavHome[1] [4, 17] projects focus on the development of adaptive control of home environments by also anticipating the location, routes and activities of the inhabitants. Intelligent prediction of such contexts helps in efficient triggering of mobility-aware services.

From information theoretic view point, an inhabitant's mobility and activity create an uncertainty of their locations and hence subsequent activities. In order to be cognizant of their contexts, the smart home needs to minimize this uncertainty as captured by Shannon's entropy measure [3]. An analysis of the inhabitant's daily routine and life style reveals that there exist some well defined patterns. Although these patterns may change over time, they are not too fre-

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[1] **M**anaging an **A**daptive **V**ersatile **Home**

quent or random, and can thus be learnt. This simple observation leads us to assume that the inhabitant's mobility or activity is a *piece-wise stationary, ergodic, stochastic process* with an associated uncertainty (entropy), as originally considered for user tracking in mobile cellular networks [1].

In an earlier work [15], we designed an optimal algorithm for location (activity) tracking in an indoor smart environment, based on dictionary management and online learning of the inhabitant's mobility profile, followed by a predictive location-aware resource management (energy consumption) scheme for a single inhabitant smart home. However, the presence of multiple inhabitants with their dynamically varying profiles as well as preferences make such tracking much more challenging. This is due mainly to the fact that the relevant contexts of multiple inhabitants in the same environment are often inherently *correlated* and *inter-independent* with each other. Therefore, the learning and prediction (decision making) paradigm needs to consider the joint (simultaneous) location tracking of multiple inhabitants. In our recent preliminary work [16], we proposed a cooperative entropy learning policy for location-aware resource management in multi-inhabitant smart homes. This approach adapts to the uncertainty of multiple inhabitants' locations and most likely routes, by varying the learning rate parameters and minimizing the Mahalanobish distance. However, the complexity of multi-inhabitant location tracking problem was not characterized which we address in this paper.

Furthermore, hypothesizing that each inhabitant in a smart home behaves in such a manner that fulfills his own objectives and maximizes his utility, the residence of multiple inhabitants with varying preferences might lead to conflicting goals. Thus, a smart home must be intelligent enough to strike a balance between multiple preferences, eventually attaining an equilibrium state. If each inhabitant is aware of the situation facing all others, a *Nash equilibrium* is a combination of deterministic or randomized choices, one for each inhabitant, from which no inhabitant has an incentive to unilaterally move away. This motivates us to investigate the multi-inhabitant location tracking problem from the perspective of stochastic game theory, where the inhabitants are the players of the game. The goal here is to achieve a Nash Equilibrium so that the system (i.e., smart home) is able to probabilistically predict the inhabitants' locations and activities with sufficient accuracy in spite of possible correlations. The major contributions of this paper are summarized below.

1.1 Contributions of This Paper

- We characterize the overall (joint) location uncertainty of multiple inhabitants in a smart environment. In particular, we prove that optimal (that attains lower bound on the entropy) tracking and hence prediction of location across multiple inhabitants is an NP-hard problem.
- Based on stochastic game theory and following the Nash Q-learning approach, we develop a novel Nash H-learning (where H stands for entropy) framework that explores the correlation of mobility patterns across multiple inhabitants and attempts to minimize the overall joint uncertainty. This is achieved by developing a new *joint utility function* of entropy. We prove that our game theoretic framework attains Nash equilibrium. Minimizing the joint utility function helps in accurate learning and estimation of inhabitants' locations and activities. We also derive worst-case performance bounds of this framework.
- While there exists an exponential number of possible routes (sequence of locations) followed by inhabitants in a smart indoor environment, we have developed an efficient scheme to predict the most likely routes jointly followed by multiple inhabitants. This scheme is based on the concept of *joint-typical-set* of sequences in information theory, that provides only a small subset of such sequences with a large probability mass.
- The knowledge of the inhabitants' contexts such as locations and associated activities, helps the smart home to control automated devices in an intelligent manner, thus providing sufficient comfort to the inhabitants. The predictive Nash H-learning framework leads to a novel mobility-aware resource management scheme that brings automation with energy consumption and hence reduces the overall maintenance cost of the smart home.
- We perform extensive experiments using real data collected from the X10 controller ActiveHome kit [7], deployed in the MavHome [18]. Experimental results demonstrate that the Nash H-learning framework performs better than predictive schemes optimized for individual inhabitants' location/activity.

The rest of the paper is organized as follows. Section 2 reviews an information theoretic approach for optimal location tracking of individual inhabitants, and its limitation in optimally handling multiple inhabitants. In Section 3 we prove that the optimal joint location prediction problem across multiple inhabitants is NP-hard. The game theoretic, Nash H-learning framework that minimizes joint uncertainty associated with multiple inhabitants, is presented in Section 4. Subsequently, we prove its convergence to Nash equilibrium and derive its worst-case performance bounds. Section 5 described how to capture the inhabitants' most likely routes. Section 6 develops a predictive resource management scheme in multi-inhabitant smart homes, based on the proposed game-theoretic framework. Experimental results in Section 7 delineates the efficiency of our framework. Finally, Section 8 concludes the paper.

2 Single Inhabitant Location Tracking

As mentioned earlier, an inhabitant's mobility creates an uncertainty of his location and thus activity. In order to minimize such uncertainty and adapt to fluctuations, one needs to build personal mobility profiles dynamically. From information theoretic perspective, *entropy* [3] is an appropriate measure to quantify this uncertainty. In the context of personal mobility tracking in cellular wireless networks, a profound result was established in [1], where the authors proved that it is impossible for any location management algorithm to track down an inhabitant by exchanging any less information, on the average, than the uncertainty generated due to its mobility. A model-independent, online compression and learning based algorithm was also proposed that minimizes location uncertainty and meets this information theoretic lower bound on entropy.

This approach was adopted in [15] for location prediction that is optimal only for single inhabitant smart homes. This predictive framework is based on *symbolic* interpretation of the inhabitant's movement (mobility) profile, as captured by sampling the in-building smart devices such as sensors, RFID readers, or pressure switches. More precisely, the inhabitant's movement history is assumed to be a string $\nu_1\nu_2\nu_3\ldots$ of symbols (e.g., sensor-ids) where ν_i is an element of the alphabet set, ϑ. Given our daily life has repetitive activity patterns, we argue that the inhabitant's current location is merely a reflection of his mobility/activity profile that can be learned over time in an on-line fashion. Characterizing such mobility as a probabilistic sequence suggests that it can be defined as a stochastic process $\mathcal{V} = \{V_i\}$. The repetitive nature of identifiable patterns (routes) adds *piece-wise stationarity* as an essential property, leading to $Pr[V_i = \nu_i] = Pr[V_{i+\ell} = \nu_i]$, for all $\nu_i \in \vartheta$ and for every shift ℓ. The family of optimal Lempel-Ziv text compression algorithms such as LZ-78 is suitable for efficient encoding of these variable length routes or contexts (substrings of symbols from the mobility profiles) such that the overall entropy is minimized. For details, refer to [1, 15].

Before proceeding further, let us formally define *entropy* and *conditional entropy* of random variables of a stochastic process from information theoretic stand point [3].

Definition 1 *For a discrete random variable X of a stochastic process, with probability mass function $p(x)$, its entropy is defined as $H(X) = -\sum_{x\in\mathcal{X}} p(x)\lg p(x)$. When $p(x) = 0$, the limiting value "$\lim_{p\to 0} p\lg p = 0$" is used.*

Definition 2 *For a set $\{V_1, V_2, \ldots, V_k\}$ of k discrete random variables with probability distribution $p(\nu_1, \ldots, \nu_k) = Pr[V_1 = \nu_1, \ldots, V_k = \nu_k]$, $\forall \nu_i \in \vartheta$, the joint entropy is given by $H(V_1, V_2, \ldots, V_k) = \sum_{i=1}^{k} H(V_i \mid V_1, V_2, \ldots, V_{i-1})$, where $H(V_i \mid V_1, V_2, \ldots, V_{i-1})$ is the conditional entropy of random variable V_i given the previous $(i-1)$ random variables $V_1, V_2, \ldots, V_{i-1}$.*

The additive terms on the right-hand side carry necessary information which makes the higher order context models more information-rich as compared to the lower order ones.

As pointed out earlier, the above location tracking strategy is optimal for individual inhabitant only. It treats every individual inhabitant independently and fails to consider the correlation between the activity and hence mobility patterns of multiple inhabitants within the same home environment. Intuitively, independent application of the above scheme for each individual actually increases the overall joint location uncertainty. Mathematically, this can be observed from the fact that *conditioning reduces entropy* [3]. In other words,

Result 1 *For a stochastic ergodic process χ containing the set of random variables $X_1, X_2, \ldots, X_n$, with distribution $Pr(X_1 = x_1, X_2 = x_2, \ldots, X_n = x_n)$,*

$$\begin{aligned} H(\chi) &= H(X_1, X_2, \ldots, X_n) \\ &= \sum_{i=1}^{n} H(X_i|X_{i-1}, \ldots, X_1) \le \sum_{i=1}^{n} H(X_i) \end{aligned}$$

In the next section, we will discuss the intricacy of location prediction problem across multiple inhabitants.

3 Multi-Inhabitant Location Prediction

The multi-inhabitant location prediction problem is defined as follows: *For a group of η predictions for η inhabitants residing in the smart home consisting of L different locations, the objective is to maximize the number of successful location predictions.* The following theorem characterizes the complexity of this problem.

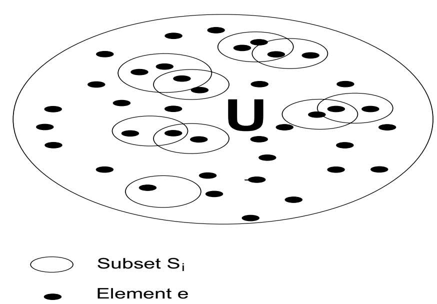

Figure 1. Analogy of Set-Packing Problem

Theorem 1 *The problem of maximizing the number of successful predictions of multiple inhabitants' locations in a smart home is NP-hard.*

Proof: We reduce this problem to the *Set Packing* problem, which is known to be NP-hard [5]. The set packing problem arises in partitioning elements under strong constraints on what is allowable partitions. The key feature is that no element is permitted to be covered by more than one set. As shown in Figure 1, the input to the Set Packing problem is a set $\mathbf{S} = \{\mathcal{S}_1, \mathcal{S}_2, \ldots, \mathcal{S}_\xi\}$ of ξ subsets of the universal set $\mathbf{U} = \{1, 2, \ldots, \eta\}$ where η is the number of prediction requests as defined above. The goal is to maximize the number of mutually disjoint subsets from $\mathbf{S}$. In other words, given the condition that each element from the universal set $\mathbf{U}$ can be covered by *at most one subset* from $\mathbf{S}$, the objective is to maximize the number of mutually disjoint subsets from $\mathbf{S}$. In order for our problem to be equivalent to the Set Packing problem, each location as identified by the sensor must be occupied by at most one inhabitant. We assume that the sensor deployment and coverage in a smart home is dense enough to make this distinction.

The maximum successful prediction process in a smart home having L locations and η prediction requests, is equivalent to the Set Packing problem with η subsets and a universal set $\mathbf{U}$ of L elements. At any instance of time, an inhabitant i can actually reside under the coverage of one or more sensors (locations), l_i. Then the prediction process, $predict_i$, for inhabitant i is a collection of its possible locations, i.e., $predict_i = \{l_i\}$. Every such prediction is mapped to a particular subset $\mathcal{S}_i$. Each single location (sensor coverage-area), l, of the home is mapped to an element, e, of a subset $\mathcal{S}_i$. The strategy that maximizes the number of successful predictions is basically the one that maximizes the number of disjoint subsets from $\mathbf{S}$.

Therefore, it is computationally infeasible to find an optimal strategy for maximizing the number of successful location predictions across multiple inhabitants. In the following, we devise a suboptimal solution based on game theory. It attempts to reach an equilibrium and maximizes the number of successful predictions across all inhabitants.

4 Predictive Nash H-learning Framework

Hypothesizing that every inhabitant wants to satisfy his own preferences about activities, we assume he behaves like a selfish agent to fulfill his own goals. Under this circumstance, the objective of the system is to achieve a suitable balance among the preferences of all inhabitants residing in the smart home. This motivates us to look into the problem from the perspective of non-cooperative game theory where the inhabitants are the players and their activities are the strategies of the game. Moreover, there can be conflicts among the activity preferences. Our proposed game theoretic framework aims at resolving these conflicts among inhabitants, while predicting their activities (and hence location) with as much accuracy as possible. Before going into the details of our framework, we briefly review the relevant concepts of game theory required for our purpose.

4.1 Stochastic Games and Equilibrium

Stochastic games model multi-agent systems where the agents are the house and the inhabitants, pursuing their individual (often conflicting) goals. We assume there exists no enforceable agreement on the joint actions of the inhabitants.

Definition 3 *[9] An n-player stochastic game, Γ, is defined as a tuple $< S, A^1, \ldots, A^n, r^1, \ldots, r^n, p >$, where S is the state space and A^i is the action space of player i; $r^i : S \times A^1 \times A^2 \ldots \times A^n \to R$ is the payoff function for player i; $p : S \times A^1 \times A^2 \ldots \times A^n \to \Delta(S)$ is the transition probability map, where $\Delta(S)$ is the set of probability distributions over state space S.*

Given a state s, the agents (inhabitants) independently perform their actions $a^1, \ldots, a^n$, for $a^i \in A^i$, and receive rewards $r^i(s, a^1, \ldots, a^n)$, for $i = 1, \ldots, n$. The state s changes to the next state s' based on transition probabilities, satisfying the constraint

$$\sum_{s' \in S} p(s'|a^1, \ldots, a^n) = 1$$

In a stochastic game, the objective of each player is to maximize the sum of rewards, with factor $\beta \in [0, 1)$. If π^i denotes the strategy of player i, then for a given initial state s, the objective of player i is to maximize the sum of rewards:

$$v^i(s, \pi^1, \pi^2, \ldots, \pi^n) = \sum_{t=0}^{\infty} \beta^t E(r_t^1 | \pi^1, \ldots, \pi^n, s_0 = s) \quad (1)$$

where $E(.)$ is the expected value.

Definition 4 *[9] A Nash equilibrium is a joint strategy where each agent is a best response to the others. For a stochastic game, each agent strategy is defined over the entire time horizon of the game. Hence, in a stochastic game Γ, a Nash equilibrium point is a tuple of n strategies $(\pi_*^1, \pi_*^2, \ldots, \pi_*^n)$ such that for all $s \in S$, $i = 1, \ldots, n$ and $\forall \pi^i \in \Pi^i$,*

$$v^i(s, \pi_*^1, \ldots, \pi_*^i, \ldots \pi_*^n) \geq v^i(s, \pi_*^1, \ldots, \pi_*^{i-1}, \pi^i, \pi_*^{i+1}, \ldots \pi_*^n) \quad (2)$$

where Π^i is the set of all strategies available to agent i.

A fundamental result related to equilibria in stochastic games states that every n-player stochastic game possesses at least one Nash equilibrium point in stationary strategies [14]. Let us now develop a suitable multi-agent learning framework that maximizes the number of successful location predictions in smart homes.

4.2 Entropy (or H) Learning

We assume that the inhabitants are fully rational in the sense that they can fully use their location histories to construct future routes. Each inhabitant i keeps a count $C_{a^j}^j$ representing the number of times an inhabitant j has followed an action $a^j \in A^j$ for a specific route in the past. When the game is encountered, inhabitant i believes the relative frequencies of each of j's movements as indicative of j's current route. So for each inhabitant j, the inhabitant i believes j plays action $a^j \in A^j$ with probability:

$$\mathcal{P}(a^j)^i = \frac{C_{a^j}^j}{\sum_{b^j \in A^j} C_{b^j}^j} \quad (3)$$

This set of route strategies forms a reduced profile of strategies Π^{-i}, for which inhabitant i adopts a best response. After the game, inhabitant i updates its possible belief of its neighbor appropriately, given the actions used by other inhabitants. We consider these counts as reflecting the observations an inhabitant has regarding the route strategy of the other inhabitants. As a result, the decision making component should not directly repeat the actions of the inhabitants but rather learn to perform actions that optimize a given reward (or utility) function.

The decision making component of a smart home uses learning to acquire a policy that optimizes overall uncertainty of the inhabitants' activities which in turn helps in accurate prediction of their locations and activities. For this optimization, our proposed entropy learning algorithm called Nash H-learning (NHL), learns a value function that maps state-action pairs to future reward using the entropy measure, H. It combines new experience with old value functions to produce new and statistically improved value functions. The proposed multi-agent Nash H-learning algorithm updates with future Nash equilibrium payoffs.

To achieve the desired performance of smart homes, a reward function, r, is defined that takes into account the success rate of achieving the goal using system beliefs. Here r is the instantaneous reward received which we have considered as the success rate of the predicted state. One measure of this prediction accuracy can be estimated from per-symbol Hamming distance which provides the normalized symbol-wise mismatch between the predicted and the actual routes followed by the inhabitants. Intuitively, this measure should have correspondence with the relative entropy between the two sequences [15].

A learning agent, indexed by i, learns about its H-values by forming an arbitrary guess at time 0. We have assumed this initial value to be zero, i.e., $H_0^i(s, a^1, \ldots, a^n) = 0$. At each time t, the agent i observes the current state and takes its action. After that, it observes its own reward, actions taken by all other agents and their rewards, and the new state s'. It then calculates a *Nash Equilibrium* $\pi^1(s'), \pi^2(s'), \ldots, \pi^n(s')$ at that stage and updates its own H-values in the form:

$$\begin{aligned} H_{t+1}^i(s, a^1, \ldots, a^n) &= (1-\alpha_t) H_t^i(s, a^1, \ldots, a^n) \\ &+ \alpha_t \left[r_t^i + \beta Nash\, H_t^i(s') \right], \\ \text{where} \quad Nash\, H_t^i(s') &= \prod_{j=1}^{n} \pi^j(s') H_t^i(s') \end{aligned} \quad (4)$$

For every agent, information about other agents' H-values is not given, so agent i must learn about those values too. Agent i forms conjectures about those H-functions at the beginning of the game. We have assumed $H_0^j(s, a^1, \ldots, a^n) = 0$, for all j and all $s, a^1, \ldots, a^n$. As the game proceeds, agent i observes other agents' immediate rewards and previous actions. That information can then be used to update agent i's conjectures on other agents' H-functions. Agent i updates its beliefs about agent j's H-function, according to the same updating rule it applies to its own. Thus, we have

$$\begin{aligned} H_{t+1}^j(s, a^1, \ldots, a^n) &= (1-\alpha_t) H_t^j(s, a^1, \ldots, a^n) \\ &+ \alpha_t \left[r_t^j + \beta Nash\, H_t^j(s') \right], \end{aligned} \quad (5)$$

Here the learning rate parameters α_t and β are in the range 0 to 1. Figure 2 describes a pseudo-code of the Nash H-learning algorithm.

```
Procedure NHL
Input:  Individual entropy values
Output:  Joint entropy values
Let the learning agent be indexed by i;
t := 0,  H_t^j(s, a^1, ..., a^n) := 0,  ∀s ∈ S and a^j ∈ A^j  ∀j
Repeat
   Choose action a_t^i;
   Compute r_t^1, ..., r_t^n,  a_t^1, ..., a_t^n and s_{t+1} = s';
   for (j := 1, ..., n),
        H_{t+1}^j(s, a^1, ..., a^n) = (1 - α_t) H_t^j(s, a^1, ..., a^n)
        +α_t [r_t^j + β Nash H_t^j(s')],
        where α_t ∈ (0,1) is the learning rate
        and Nash H_t^j(s') = ∏_{k=1}^n π^k(s') H_t^j(s')
   t := t + 1;
until (true)
```

Figure 2. Nash H-learning algorithm (NHL)

4.3 Convergence of NHL Algorithm

The convergence proof is based on two basic assumptions:

1. Every state $s \in S$ and action $a^k \in A^k$ for $k = 1, \ldots, n$ are visited infinitely often.

2. The learning rate α_t satisfies the following conditions: $0 \le \alpha_t(s, a^1, \ldots, a^n) < 1$; and $\alpha_t(s, a^1, \ldots, a^n) = 0$ if $(s, a^1, \ldots, a^n) \ne (s_t, a_t^1, \ldots, a_t^n)$. In other words, the updates of H-functions occur only at the current state.

Our proof relies on the following result, which establishes the convergence of a general functional-learning process updated by a pseudo-contraction operator, P_t. Let $\mathcal{U}$ be the space of all utility functions.

Result 2 *[9]: Let there exist a number γ such that $0 < \gamma < 1$ and a sequence $\lambda_t \ge 0$ converging to zero with probability 1 such that $|P_t U - P_t U_*| \le \gamma |U - U_*| + \lambda_t$ for all $U \in \mathcal{U}$ and $U_* E[P_t U_*]$. Then the following condition holds:*

$$Pr\left[(U_{t+1} = (1-\alpha_t) U_t + \alpha_t [P_t U_t]) \to U_* \right] = 1 \quad (6)$$

In other words, we can say that the iterative utility function U_t converges to the Nash Equilibrium U_* with probability 1.

Replacing the general utility function U by entropy-function corresponding to H-learning, we get

$$Pr\left[(H_{t+1} = (1-\alpha_t) H_t + \alpha_t [P_t H_t]) \to H_* \right] = 1.$$

For our n-player stochastic game we define the operator P_t as:

$$\begin{aligned} P_t H^k(s, a^1, \ldots, a^n) &= r_t^k(s, a^1, \ldots, a^n) + \beta \pi^1(s') \ldots \\ &\quad \pi^n(s') H^k(s'), \text{ for } k = 1, \ldots, n, \end{aligned} \quad (7)$$

where s' is the state at time $t+1$ and $\pi^k(s')$ is an equilibrium strategy at that stage of the game corresponding to the utility function $H^k(s')$. We now state the main result along with its proof:

Result 3 *For a n-player stochastic game in smart homes,* $E[P_t H_*] = H_* = (H_*^1, \ldots, H_*^n)$

Proof: If $v^k(s', \pi_*^1, \ldots, \pi_*^n)$ is an agent k's equilibrium payoff and $(\pi_*^1(s), \ldots, \pi_*^n(s))$ is its Nash Equilibrium point, then the sum of rewards $v^k(s', \pi_*^1, \ldots, \pi_*^n) = \pi_*^1(s), \ldots, \pi_*^n(s) H_*^k(s')$ according to [9]. Based on this relation, we can state that

$$\begin{aligned} H_*^k(s', a^1, \ldots, a^n) &= r^k(s, a^1, \ldots, a^n) + \\ \beta \sum_{s' \in S} p(s'|s, a^1, \ldots, a^n) &\pi_*^1(s') \ldots, \pi_*^n(s') H_*^k(s') \\ = \sum_{s' \in S} p(s'|s, a^1, \ldots, a^n) &\times [r^k(s, a^1, \ldots, a^n) + \\ \beta p(s'|s, a^1, \ldots, a^n) &\pi_*^1(s') \ldots, \pi_*^n(s') H_*^k(s')] \\ &= E\left[P_t^k H_*^k(s, a^1, \ldots, a^n)\right] \end{aligned} \quad (8)$$

Combining Equations (6)–(8), we conclude:

Result 4 *The predictive H-learning framework given by the iterative Equation (5) almost surely converges to Nash-Equilibrium. Thus,*

$$Pr\left[H_{t+1} \rightarrow H_*\right] \rightarrow 1,$$

$$\textit{where } H_{t+1} = (1-\alpha_t) H_t + \alpha_t \left[r_t + \beta \prod_{j=1}^{n} \pi^j(s') H_t(s') \right] \quad (9)$$

4.4 Worst-Case Analysis

In a smart home environment, multiple inhabitants act autonomously without an authority regulating their day-to-day activities in order to achieve some "social optimum" such as minimization of overall joint uncertainty across all inhabitants' locations and activities. In our system where multiple inhabitants share a common resource, we use the ratio between the worst possible Nash equilibrium and social optimum as a measure of the effectiveness of the system. Basically, we are investigating the cost of the lack of *coordination* as opposed to the lack of *information* (on-line algorithms) or lack of *unbounded computational resources* (approximation algorithms). The basic assumption in our framework is that every inhabitant always attempts to benefit from the underlying utility function associated with him. Now the question is: how much performance is lost because of this? The answer to this question provides the basis for *worst-case analysis* or *coordination ratio*, given by the ratio of worst possible cost and optimal cost. Note that, although Nash Equilibrium attains a balance between the preferences of all inhabitants, it is not necessarily optimal. The deviation from optimality in this environment can be estimated using this worst-case analysis.

Result 5 *The worst-case coordination ratio for m inhabitants taking m actions is given by* $\Omega\left(\frac{\lg m}{\lg \lg m}\right)$.

Proof: The problem is identical to that of throwing m balls in m bins and attempting to find expected maximum number of balls in a bin. The bound follows from [10].

We believe that this lower bound is tight and if T_m denotes the expected maximum number of balls in a bin, we conjecture that the coordination ratio of any number of inhabitants taking m actions is also T_m.

Theorem 2 *The coordination ratio of any number of inhabitants with m actions is at most* $T = 3 + \sqrt{4m \lg m}$

Proof: A quantity associated with an equilibrium in our context is the expected entropy over all actions for a specific route. From this perspective, inhabitant i maintains beliefs about the strategy of other inhabitants and predicts the Expected Entropy Value (EEV) of its individual action a^i at $(t+1)$-th time step as follows:

$$\begin{aligned} EEV_{t+1}^i(a^i) = \sum_{a^{-i} \in A} & H_{t+1}^i\{(s, a^1, \ldots, a^n) \\ & \cup (s, a^{-1}, \ldots, a^{-n})\} \prod_{j \neq i} \mathcal{P}(a^{-i})^j \end{aligned} \quad (10)$$

We call it the Nash equilibria cost which we wish to compare with the social optimum entropy, Ψ. More precisely, we want to estimate the coordination ratio as the worst case ratio $C = \max\{\text{Nash equilibria cost} / \Psi\}$ where the maximum ia taken over all equilibria. Computing the social optimum (Ψ) is an NP-hard problem (equivalent to partition problem, see Theorem 1). However, for the purpose of upper bounding C, it suffices to use two simple approximations: $\Psi \geq \max\{H_{t+1}^i(s, a^1, \ldots, a^n), EEV_{t+1}^i(a^i)/n\}$

Using a martingale concentration bound known as the Azuma-Hoeffding inequality [6], we will show that the utility (entropy) of a given action j exceeds $(T-1)\Psi$ with probability at most $\frac{1}{m^2}$. Then, the probability that the maximum utility on all actions does not exceed $(T-1)\Psi$ is at least $\frac{1}{m}$. It follows that the expected maximum utility is bounded by $(1-\frac{1}{m})(T-1)\Psi + \frac{1}{m}(m\Psi) \leq T\Psi$. It remains to show the probability that the utility of a given action j exceeds $(T-1)\Psi$ is indeed small, at most $\frac{1}{m^2}$.

Let X_i be a random variable denoting the contribution of inhabitant i towards the utility of action j. In particular, $Pr[X_i = H_1] = \mathcal{P}$ and $Pr[X_i = 0] = 1 - \mathcal{P}$. Clearly, the random variables $X_1, \ldots, X_n$ are independent. We are interested in estimating the probability $Pr[\sum X_i \geq (T-1)\Psi]$. Since the entropy H_{t+1} and probabilities $\mathcal{P}$ may vary a lot, we do not expect the sum $\sum X_i$ to exhibit the good concentration bounds of sum of binomial variables. However, we can get a weaker bound using Azuma-Hoeffding inequality which gives very good results for probabilities around 0.5. In our case, the probabilities are either 0 or 1.

Let $\mu_i = E[X_i]$ and consider the martingale $S_t = X_1 + \ldots + X_t + \mu_{t+1} + \ldots + \mu_n$. Now notice that $\mid S_{t+1} - S_t \mid =$

$|X_{t+1} - \mu_{t+1}| \leq H_{t+1}$. We can then apply the Azuma-Hoeffding's inequality:

$$P[S_n - E(S_n) \geq x] \leq exp(-\frac{1}{2}x^2 / \sum_i {H_{t+1}^i}^2)$$

Let $x = (T-3)\Psi$. Since $E(S_n) = \sum \mu_i = EEV_{t+1}^i(a_i) \leq 2\Psi$, we get that the entropy of action j exceeds $(T-1)\Psi$ with probability at most $exp(-\frac{1}{2}x^2 / \sum_i {H_{t+1}^i}^2)$. It is easy to establish that

$$\sum_i {H_{t+1}^i}^2 \leq \max\{mH_1^2, m(\sum_i H_{t+1}^i / m)^2\} \leq m\Psi^2$$

Thus, the probability that the entropy of action j exceeds $(T-1)\Psi$ is at most $exp(-\frac{1}{2}(T-3)^2/m)$. For $T = 3 + \sqrt{4m \lg m}$, this probability becomes $1/m^2$ and the proof is complete [10].

5 Inhabitants' Joint-Typical Routes

The collection of indoor locations inside the smart homes actually forms the routes (paths) of the inhabitants. Although there may be an exponential number of possible routes in general, the inhabitants typically follow only a small subset of these paths reflecting their mobility profiles in the long run. The concept of *jointly-typical set* and *asymptotic equipartition property* (AEP) [3] from information theory helps derive this *small subset* of *highly probable* routes maintained by a particular inhabitant.

While the concept of jointly-typical set is valid for any number of sequence-sets, for the sake of simplicity, we explain with the help of only two sets of sequences. Let $\mathcal{Z}$ and $\mathcal{Y}$ denote discrete and finite sets, and let $Pr_{\mathcal{Z},\mathcal{Y}}$ be a probability mass function on $\mathcal{Z} \times \mathcal{Y}$. Let $z^n = (z_1, \ldots, z_n)$ denote an n-length sequence of symbols from $\mathcal{Z}$, i.e, $z^n \in \mathcal{Z}^n$. Similarly, let y^n denote elements of $\mathcal{Y}^n$. Also let, $(\mathcal{Z}^n, \mathcal{Y}^n) = [(\mathcal{Z}_1, \mathcal{Y}_1), \ldots, (\mathcal{Z}_n, \mathcal{Y}_n)]$ denote an n-length sequence of random variables drawn according to the product measure on $\mathcal{Z}^n \times \mathcal{Y}^n$ obtained from $Pr_{\mathcal{Z},\mathcal{Y}}$. Then $Prob[Z^n = z^n, Y^n = y^n] = Pr_{Z^n,Y^n}(z^n, y^n)$ $= \prod_{i=1}^n Pr_{Z,Y}(z_i, y_i)$.

Result 6 *The set of jointly typical sequences* $\mathcal{T}_\epsilon^{(n)} = \{(z^n, y^n) \in \mathcal{Z}^n \times \mathcal{Y}^n\}$ *for the joint probability mass function (pmf)* $Pr_{Z,Y}$ *is a set of sequences which hold the following relations* $|\frac{-1}{n} \lg Pr_{Z^n,Y^n}(z^n, y^n) - H(Z,Y)| \leq \epsilon \Rightarrow |\frac{-1}{n} \lg Pr_{Z^n}(z^n) - H(Z)| \leq \epsilon$ *and* $|\frac{-1}{n} \lg Pr_{Y^n}(y^n) - H(Y)| \leq \epsilon$.

The most important feature of the joint-typical set is that it is sufficiently small and contains most of the probability mass of the set of sequences; i.e., $Pr[(Z^n, Y^n) \in \mathcal{T}_\epsilon^{(n)}] \to 1$. This is basically the *Asymptotic Equipartition Property* (AEP) [3] for stationary ergodic process. This encompasses the inhabitant's most likely routes and determines the *average nature* of the large route-sequences.

If $Pr[\phi_1, \phi_2]$ denotes the joint-probability of the two inhabitants' contexts (routes) Y and Z, each of length $\mathcal{L}(\phi)$, their *probabilistic difference* is computed as: $\delta = |Pr[\phi_1, \phi_2] - 2^{-\mathcal{L}(\phi)H(Z,Y)}|$. Clearly, δ provides the gap between the ideal probability of typical routes and the probability of a particular route stored in the dictionary. Choosing a higher value of δ leads to the inclusion of a large number of *typical* mobility-profiles and the framework starts deviating from the typical-set of routes. In our experiments, we have used $\delta \leq 0.01$. Thus, the system captures a typical set of inhabitant's movement profiles from the H-learning scheme and uses them to predict the inhabitants' most likely routes.

6 Resource and Comfort Management

The objectives of a smart home include how to efficiently automate device control, provide the inhabitants with maximum possible comfort, minimize operation cost and consumption of resource, say energy. By managing the uncertainty related to the inhabitants' location and activity, the house becomes intelligent enough to make more accurate prediction of inhabitants' activities that help smart control of automated devices and appliances. Reduction in explicit manual operations and control, in turn, increases the inhabitants' comfort. In the following, we develop a mobility-aware resource management scheme for multiple inhabitant smart homes. Minimizing energy consumption reduces the maintenance cost.

6.1 Mobility-Aware Energy Conservation

Let us first consider two simple but extreme energy management schemes. In the worst-case scenario, a house may use a static scheme where a certain number of devices (electric lights, fans, etc.) are kept on for a fixed amount of time during a day. Intuitively, this results in unnecessary energy consumption. On the other hand, in the best-case scenario, devices are manually controlled every time while leaving or entering particular locations inside the house. However, such manual operations are against the smart home's goals of building intelligence automation and providing comfort to the inhabitants. We believe a smart energy management scheme ought to use predictive routes and activities for smart control of devices, thus minimizing unnecessary consumption of valuable resources. Devices like lights, fans or air-conditioner operate in a *pro-active* manner to conserve energy during the inhabitant's absence in specific locations in the home. These devices also attempts to bring the indoor environment such as temperature and light control, to amicable conditions before the inhabitant actually enters into those locations.

Let $\mathcal{Q}_{ij}$ denote the power of i^{th} device in j^{th} zone, ψ denote the maximum number of devices which remained turned on in a particular zone, $\mathcal{R}$ denote the number of zones, $t_1 \leq t \leq t_2$ denote the time during which the device remains turned on, and let $p(t)$ denote the probability density function of uniform time distribution. Then the expected average energy consumed ($\mathcal{E}$) due to lights and de-

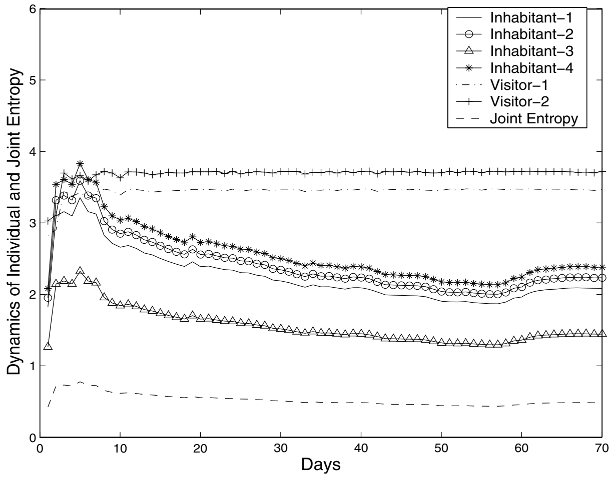

Figure 3. Entropy using H-learning

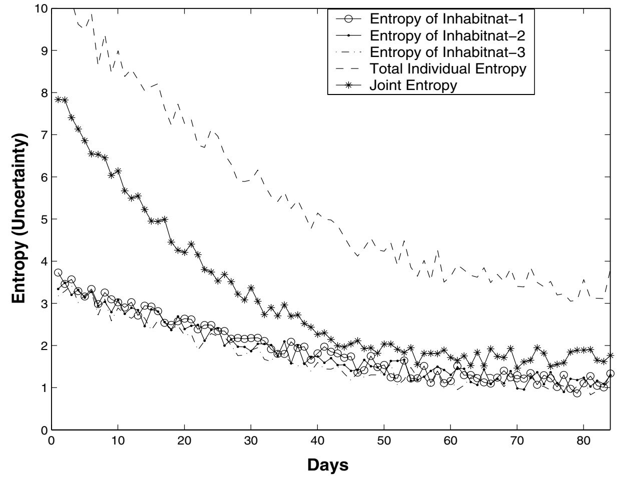

Figure 4. Entropy using Nash H-learning

vices will be: $\mathcal{E} = \frac{t_2 - t_1 + \Delta_t}{2} \sum_{j=1}^{\mathcal{R}} \sum_{i=1}^{\psi} \mathcal{Q}_{ij}$, where Δ_t is the interval between the time for predictive device operation and entry time of the first inhabitant in the zone.

6.2 Smart Temperature Control

We have developed a distributed temperature control system with a goal to conserve energy. This control system is intelligent enough to bring the temperature of specific locations (inside the home) to an amicable level before an inhabitant enters those locations. The operation of temperature control is termed as *preconditioning*, the time required is called *preconditioning period*, and the *rate of energy* required during this period is known as *preconditioning load*. The predictive location management scheme estimates the most probable jointly-typical-set of routes and near future locations. For a specific pre-conditioning period, W_T, the constant rate of energy at full capacity is supplied to bring down the temperature to the appropriate comfort level. The shorter the duration of W_T, the larger is the preconditioning load. In order to estimate this preconditioning load, it is required to know the characteristics of air temperature variation caused by constant unit rate of heat extraction from the specific locations. This temperature variation and preconditioning period can be estimated using *Newton's Law of Cooling*, which states that the temperature changes at a rate proportional to the relative temperature of the surroundings. Thus, if $\theta(t)$ denotes the temperature at time t, then according to this law: $\frac{d\theta(t)}{dt} = -k(\theta - \tau) \; => \; \theta(t) = \tau + (\theta_0 - \tau)e^{-kt} \; => \; k(t_1 - t_2) = -\; ln \left[\frac{\theta(t_1)-\tau}{\theta(t_2)-\tau}\right]$. In the cooling mode, once the air conditioning is stopped (inhabitant's departure from specific location of the house), the temperature of that region increases rapidly. The same mechanism is repeated whenever the inhabitant is about to move into the specific locations inside the house. The preconditioning period is followed by the conditioned period, when the room temperature is kept constant at a reference level.

6.3 Estimation of Inhabitants' Comfort

The comfort is a subjective measure experienced by the inhabitants, and hence quite difficult to derive analytically. In-building climate, specifically temperature, plays an important role in defining comfort. Moreover, the number of manual operations and the time spent by the inhabitants in performing daily activities also contribute to the inhabitants' comfort. We define the comfort as a joint function of temperature deviation, $\Delta(\theta)$, number ($\mathcal{M}$) of manual device operations, and time (τ) spent for those activities by the inhabitants. Thus, $Comfort = f\left(\frac{1}{\Delta(\theta)}, \frac{1}{\mathcal{M}}, \frac{1}{\tau}\right)$.

Our mobility-aware resource management framework attempts to reduce empirical values of these controlling parameters, thereby increasing the inhabitants' comfort. Note that the reduction of joint entropy by using our proposed NHL algorithm described in Figure 2, endows the house with sufficient knowledge for accurate estimate of current and future contexts (locations, routes and activities) of multiple inhabitants in the house. Successful estimate of these contexts results in adaptive control of environmental conditions and automated operation of devices.

7 Experimental Study

In this section, the proposed Nash H-learning framework is implemented and we conduct a series of experiments to study its performance on a group of three inhabitants in a smart home equipped with smart devices and wireless sensors. The inhabitants wear rado frequency identification (RFID) tags and are tracked by RFID-readers. The house is equipped with explicit monitoring of inhabitants' activities and locations for performing a trace-driven simulation of the inhabitant's mobility followed by the resource management scheme.

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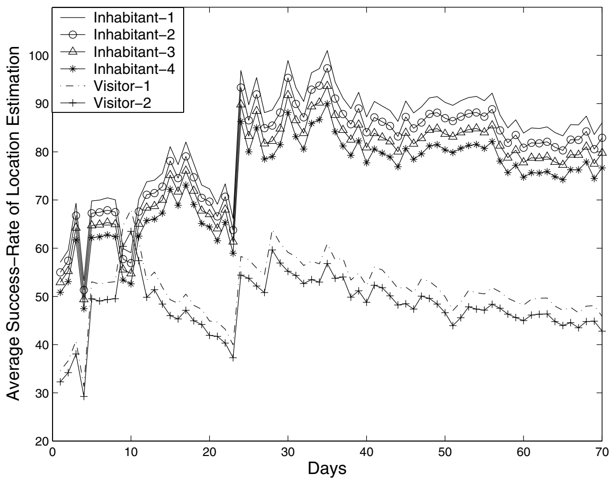

Figure 5. Prediction Success using H-learning

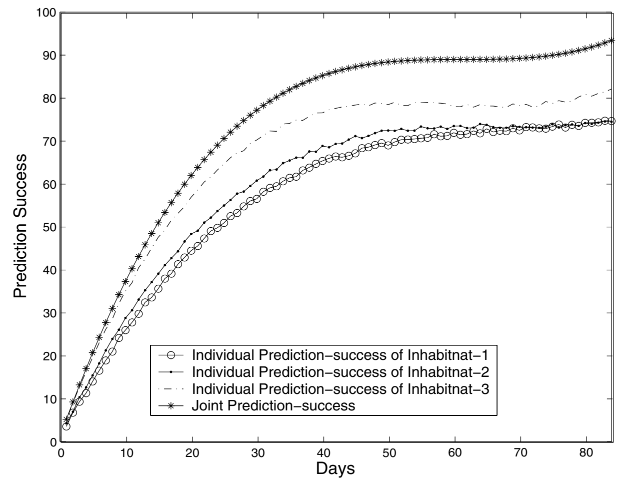

Figure 6. Prediction Success using Nash H-learning

7.1 Simulation Environment

We have also developed an object-oriented discrete-event simulation platform for generating and learning inhabitants' mobility profiles, and predict the likely routes that aid in the resource and comfort management scheme. In order to collect the inhabitant data associated with his life-style for testing, the appliances in the MavHome are equipped with $X10$ ActiveHome kit and HomeSeer [7], thus allowing the inhabitant to automatically control the appliances. The identity of the inhabitants, their locations and activities are captured by wireless sensors placed inside the home. The inhabitants wear the RF-tags, which are sensed by the RF-readers to gather their identities. The sensors placed in the smart home work in coordination with RF-readers to explicitly monitor the activities of the inhabitants inside the home. The raw data [17][18] as shown in Table 1 is first parsed using parsing tools like Perl and Tcl to remove unnecessary information. The different column headings from the table have the following meanings: Mark as time stamp, Zone and Number as unique sensor identifier, State as binary 'on' or 'off' of the sensor, Level as specific value if on, Source as the network mode. Subsequently, we use that data to validate the mobility-aware resource management scheme. The energy and comfort management framework is compared with two reference platforms: (i) energy management without any predictive scheme, and (ii) energy management associated with per-inhabitant location prediction. The results are presented by sampling every sensor at a time and performing simulation experiments for a period of 12 weeks over 4 inhabitants and 2 visitors.

7.2 Performance Results

We resent the set of simulation results into three categories. First, we demonstrate the accuracy of our proposed predictive framework in multi-inhabitant smart homes and compare the results of the proposed Nash H-learning framework with a simple H-learning algorithm [16]. We also show the storage and computational overhead associated with the framework. Finally, we discuss its advantage in terms of energy conservation and inhabitants' comfort.

Table 1. A snapshot of the collected raw data

Mark	Zone	Number	State	Level	Source
$09:47:30$	i	5	1	100	$X10$
$13:04:45$	a	1	1	100	$X10$
$13:06:22$	c	4	0	0	$X10$
$13:16:32$	S	1	1	10	$ArgusMS$
$13:16:33$	S	2	1	152	$ArgusMS$
$23:59:04$	V	21	0	0	$ArgusD$
$23:59:12$	V	21	1	100	$ArgusD$
$23:59:12$	V	21	0	0	$ArgusD$

7.2.1 Predictive Location Estimation

Recall that the Nash H-learning framework aims at reducing the location uncertainty (entropy) associated with individual as well as multiple inhabitants. Figure 3 shows the variation of the individual and joint entropy over the entire time period of the simulation using the H-learning approach which reduces the joint entropy quickly to a low value. While the entropy of a resident inhabitant lies in the range $\sim$ 1–3, the visitor's entropy is typically higher, for example ~ 4. This is because the house finds the location contexts of the visitors more uncertain than the residents. In comparison, Figure 4 shows that initially the entropy associated with all three individual inhabitants is around 4.0 using the Nash H-learning framework. As this predictive framework gains knowledge about the inhabitants' life-style, the individual entropy values reduce to 1.0. Therefore, the joint

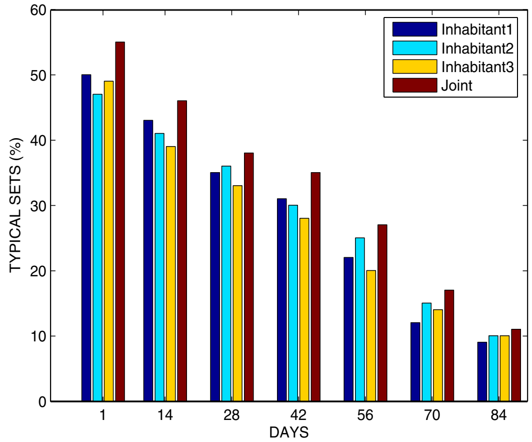

Figure 7. Dynamics of Typical Routes

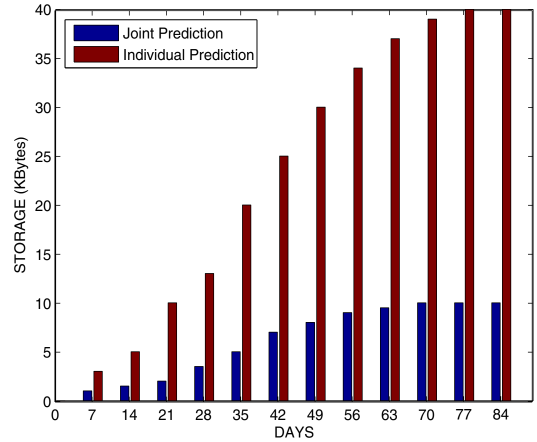

Figure 8. Storage Overhead

entropy is quite less than the total entropy of all the inhabitants. Initially, the joint entropy value is close to 8.0, but gradually it reduces to almost 1.0. The total entropy, on the other hand, lies in the range 4.0–10.0. In this way, the entropy minimization procedure formulated by Nash H-learning helps increase the efficiency of the location estimation technique.

The goal of our first experiment is to investigate into the dynamics of this entropy. The Nash H-learning framework also leads to higher success rate than simple H-learning. Figure 5 demonstrates that our co-operative H-learning strategy is capable of estimating the location of all the resident inhabitants with almost 90% accuracy within 3 weeks span. The house takes this time to learn the joint movement patterns of all inhabitants. The success rate of location estimation for visitors is however 50%–60%. In contrast, Figure 6 shows the variation of prediction success for individual inhabitants and joint prediction success using Nash H-learning framework. Initially, the success-rate is pretty low as the system proceeds through the learning stage. Once the system becomes cognizant of inhabitants' profiles, the success-rate increase and saturates at a particular value. The individual prediction process does not consider the correlation among different inhabitants. Thus, it fails to capture some important contexts and results in comparatively lower prediction success upto 80%. The joint prediction, however, takes the correlation among different inhabitants into account and results in higher success rate (close to 95%) than the simple H-learning framework.

The collection of the inhabitants' joint typical-set is the key behind the development of efficient energy and temperature control system in the smart home. As discussed earlier, this joint-typical set is a comparatively small subset of all routes (of all inhabitants) containing most of the probability mass (i.e., set of most probable routes). Figure 7 provides the percentage of total routes categorized as individual and joint typical routes. We observed that the size of the individual and joint typical set is initially less than 50% of total routes. This size then gradually shrinks to as low as about 10% as the system captures the relevant contexts of the inhabitants' movement profiles.

7.2.2 Energy Savings and Comfort

With a goal to maximize the inhabitants' comfort with minimum energy consumption, the predictive framework makes the system knowledgeable of the inhabitants' profiles. The smart temperature control system with the energy management scheme makes intelligent use of these profiles to conserve energy. Figure 9 shows that using the predictive framework, the daily average energy consumption can be kept about 4 KiloWatt-hour (KW-Hr), in comparison with 20 KW-Hr without predictions. Figure 10 shows the reduction of manual operations and time spent for all the inhabitants. The Nash H-learning framework aids the system with sufficient automation, by reducing the overall manual operations performed by the inhabitants and the time spent behind all such operations which in turn increases the overall comfort.

Remark: We observe from Figure 8 that our multi-inhabitant, joint prediction scheme based on the Nash H-learning framework has low storage (memory) overhead. In particular, the storage required for joint location prediction is about 10 Kbytes, compared to the total storage of about 40 Kbytes for the existing per-inhabitant prediction scheme [15]. Moreover, the average time complexity per day in the smart home for the multi-inhabitant framework is reduced by 40%.

8 Conclusion

In this paper, we have developed a novel mobility-aware resource management framework in a multi-inhabitant

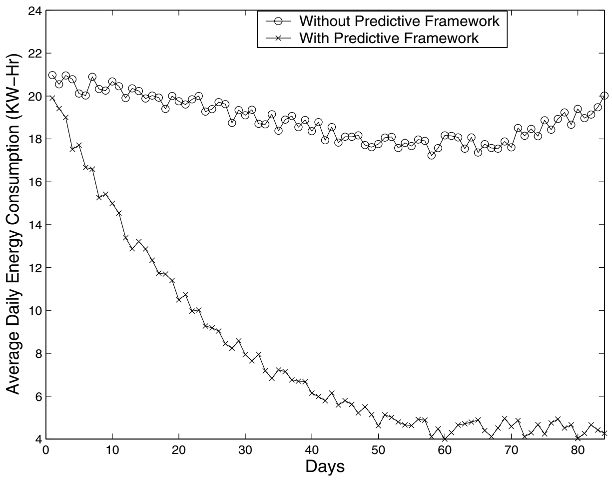

Figure 9. Energy Consumption

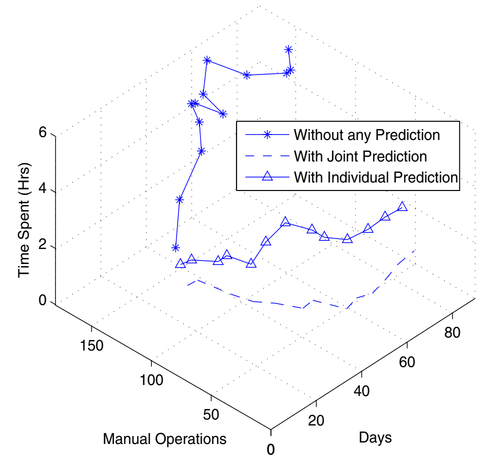

Figure 10. Manual Operations and Time Spent

smart home. Characterizing the mobility of inhabitants as a stationary, ergodic, stochastic process, the framework uses the information theoretic measure to estimate the uncertainty associated with all the inhabitants in the house. Recognizing that the direct use of per-inhabitant location tracking fails to capture the correlation among multiple inhabitants' locations or activities, we have proved that the multi-inhabitant location tracking is an NP-hard problem. We also formulated a non-cooperative learning paradigm based on stochastic game theory, which learns and estimates the inhabitants' most likely location (route) profiles by minimizing the overall entropy associated with them. The convergence and worst-case performance bounds of this framework are also derived. Automated activation of devices along the predicted locations/routes provide the inhabitants with necessary comfort while minimizing energy consumption and cost.

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