A Stochastic Scheme to Balance Power Saving and Response Time of Electronic Devices

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Abstract. This paper proposes a stochastic scheme called Gynapse which balances power saving and response time by switching electronic devices between different power modes. Gynapse predicts the wake-up probability of each device on the basis of a Hierarchical Hidden Markov Model. With the predicted probability, required response time, and device power consumption as inputs, Gynapse uses our novel optimization method to manage power mode switching, and thereby minimizes total energy consumption while ensuring response time does not exceed the required level.

1 Introduction

Power consumption has become a serious concern when people use electronic devices. However, reductions in power consumption should not be achieved at the expense of user experience. Harris and Cahill point out the necessity of minimizing power consumption while maintaining user-perceived device performance and focus on reducing PC power consumption based on predicted usage probability [1]. Harle and Hopper take response time as a key performance measure and investigate the power saving potential of location-awareness system for three "response time" categories of office device [2].

In this paper, we propose a stochastic scheme called Gynapse to trade off power saving and response time by switching electronic devices between different power modes. The idea is depicted in Fig. 1. Although the device can save energy in power-saving mode, the user must wait $T_5 - T_4$ after performing a request, which is equal to the device's wake-up time T_{WU}. If we were able to properly forecast the request at T_4, the device could be awoken before that, and the response time $T_5^{'} - T_4$ would be shortened. If the user requires a response time not in excess of a maximum value T_{RS}, the device must awoken at least $T_{WU} - T_{RS}$ before his request at T_4. This is also the optimal wake up time for this device, where power consumption is minimized and the response time is within the required range.

The difficulty here is in achieving the total optimization of multiple devices with different wake-up times. Our contribution is in solving this problem with a prediction and optimization framework: at time t, a Hierarchical Hidden Markov

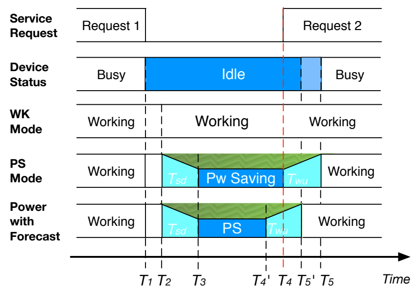


Fig. 1: Power Saving Mechanism

Model (HHMM) is built to predict device i's probability of being in a working mode at time $t+(T_{WU,i}-T_{RS,i})$, which is the probability that device i should be awoken at t. While in previous research wake-up depends *solely* on the predicted probability, we use the probability to filter out several "possible" scenarios, select the one that minimizes total power consumption as an "optimal" scenario, and then wake up devices based on it. In this way, total power consumption can be minimized and the response time will not exceed the required level.

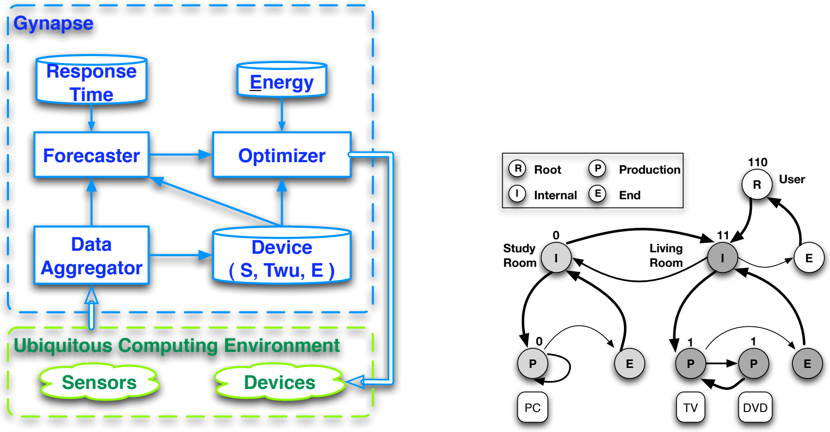
2 Gynapse

We will use a hypothetical environment to describe our system: a user has a TV and a DVD player in her living room and a PC her study. For brevity, *1* is used to indicate a working mode (WK), and *0* is used to indicate a power-saving mode (PS). Therefore, in scenario *101* means TV is in WK, DVD is in PS, and PC is in WK.

A conceptual system architecture is depicted in Fig. 2 (a). The Data Aggregator receives information from different types of sensors/devices with different data frequency, normalizes their values to a range between 0 and 1, and builds them into a time series. The Forecaster receives these time series and required response times to forecast the wake-up probability of each device based on a three-level HHMM. With the predicted probability, current status, and power consumption of devices, the Optimizer handles power mode switching to maximize the total power saving while ensuring that response time does not exceed the required level.

2.1 Forecaster

The hierarchical nature of HHMMs easily characterizes natural hierarchies in human activity and allows for model reusability and more efficient learning [3, 4]. Accordingly, we use a three-level Hierarchical Hidden Markov Model to represent device usage. Fig. 2 (b) illustrates an example: one node at root level represents scenario *110*. Two nodes at the 2^{nd} level represent the status of the living room *11* and study room *0*. Three nodes at the 3^{rd} level represent the status of the TV *1*, DVD *1*, and PC *0*.



(a) System Architecture (b) 3-Level HHMM

Fig. 2: Gynapse

We divide the whole process into two phases: Learning and Predicting. In the Learning phase, the HHMM parameters are estimated from historical data. Then, based on these learned parameters, the Forecaster predicts p_i, the wake-up probability of device i. The problem of devices having different wake-up times can be solved by multiplying different times of transition matrix. The Forecaster then sends the respective values of p_i to the Optimizer, such as $p_{TV} = 0.90$, $p_{DVD} = 0.55$, and $p_{PC} = 0.20$.

2.2 Optimizer

After receiving the predicted probability, the Optimizer first calculates the probability of all scenarios. For instance, the probability of scenario *110* is $p_{TV} \times p_{DVD} \times (1 - p_{PC}) = 0.90 \times 0.55 \times (1 - 0.20) = 0.396$, and the probability of *100* is 0.324. These two with the highest probabilities are selected as "possible" scenarios, and their total power consumptions are computed as:

$$E = 1 \times e_{TV} + 1 \times e_{DVD} + 0 \times e_{PC} \qquad E = 1 \times e_{TV} + 0 \times e_{DVD} + 0 \times e_{PC} \tag{1}$$

where e_i is the power consumption of device i. The Optimizer selects the scenario with the minimum power consumption as "optimal". Because no forecast algorithm guarantees 100% correctness, this method does not depend *merely* on probability. Instead, it takes a different perspective: since the user will be satisfied as long as response time requirements are fulfilled, we can minimize total power consumption under this constraint with respect to user requirements.

Then, the Optimizer compares the current scenario with the selected optimal scenario. For instance, if the current scenario is *101*, while the selected scenario is *100*, the Optimizer will transition the PC into power-saving mode to reduce total energy consumption.

3 Preliminary Results

We used sensor data from MIT PlaceLab [5] to evaluate our system, which has totally 37 current sensors. We used the four current sensors in living/study room to collect power consumption data of five devices: Light_L in the living room, Light_S in the study, TV and DVD in the living room, and PC in the study. Another 21 sensors in these two rooms are used as points of observation, which include two light sensors, three humidity sensors, seven switch sensors, one pressure sensor, and eight temperature sensors. For each time step, Gynapse forecasts the wake-up probability of five devices, and optimizes power mode switching to minimize total power consumption. Fig. 3 shows the real and optimized results for these devices. Total energy savings is 3.4%, and respective energy savings from each device are: Light_L 11.2%, Light_S 10.9%, TV 0.6%, DVD 0.0%, and PC 1.2%.

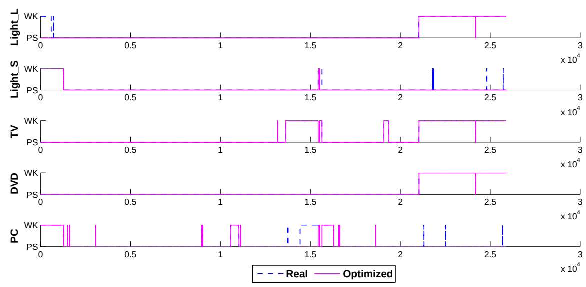


Fig. 3: Real and Optimized States for Respective Devices

4 Conclusion

In this paper, we have presented a stochastic scheme called Gynapse to trade off power saving and response time by switching electronic devices between different power modes, and have explained the details of forecaster and optimizer. Although the total energy saving are not large, the preliminary results demonstrated that power saving can be achieved especially for devices with large wattage difference between working and power saving modes. We look forward to experimenting with all 37 current sensors in PlaceLab and believe more energy savings can be achieved.

Acknowledgement This work is supported by Ministry of Internal Affairs and Communications, Japan (Ubiquitous ServicePlatform)

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