The Adaptive House

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Home automation

Homes might be programmed to

- close drapes at night
- turn down stereo volume when phone rings
- flash bathroom lights as reminder to take medication
- draw a bath at a certain temperature at a certain time

Vision of the future

...Imagine that the owner of a new home does not plan on using his lower level much at night. He can have a technician at the central station program his system so that the temperature is lowered to 60° at 10 p.m. But later, a home theater is installed in the basement, and many late weekend evenings are spent watching laser-discs and videos. The owner can simply call the technician and request that the program be changed so that the lower level remains a comfortable 72° on Friday and Saturday nights. (Electronic House)
The failure of home automation

“Homes get smart with automation systems”, USA Today, 9/2/97

Before retiring for the night, for example, the Alexanders will set a hello or morning mode, which will wake the family at 7 a.m. to lights, music, or television morning shows. Coffee begins brewing. The thermostat adjusts for family comfort. The hot water kicks in, and hot water fills the tub...

“Our biggest problem so far has been in forgetting to activate the home mode when we arrive home at the end of the day,” says Alexander. “My wife, in particular, likes to take a hot bath and the end of her work day, but if she or I forget to press the home mode, there won’t be any warm water in the hot water heater for her bath because we’ve turned off the appliance during the day to conserve electricity.”

“The smart house”, San Francisco Examiner, 4/14/96

“When I consider all the aggravation and the money, I wouldn’t spend as much again the next time, said Tiburon homeowner Bob Becker. In 1991, he built a high-tech castle atop a hill...with about $70,000 in electronic upgrades.

“I use about half of it,” said Becker...

Interview with Martha Stewart, in Wired, 8/98

Q: Any thoughts on smart houses? How about having your refrigerator talk to your stereo?

A: I don’t want my refrigerator talking to me period. I don’t want it telling me that I am low on meat-balls. I do have a brain.
State of the art in lighting control

Up at 7 a.m... in bed at 11 p.m.—if your schedule falls into a predictable routine like this, the SS7C 7-Day Wall Switch Timer from Intermatic offers a simple way to put the bedroom lights on automatic pilot.

The Brilliance II keypad from Lightolier
The adaptive house

Not a programmable house, but a house that programs itself.

House adapts to the lifestyle of the inhabitants.

House monitors environmental state and senses actions of inhabitant.

House learns inhabitants’ schedules, preferences, and occupancy patterns.

House uses this information to achieve two objectives:
(1) anticipate inhabitant needs
(2) conserve energy

Domain: home comfort systems

- air heating
- lighting
- water heating
- ventilation
Tremendous potential cost/energy savings

- Single set back period on furnace: 9–18%
- Multiple set back periods: 25–30%
- Set back (electric) water heater: 25%
- Shift majority of electric use off peak: 20–40%
The adaptive house

Residence in Marshall, Colorado, outside of Boulder
Some of the gang
Great room
Bedrooms and bathrooms
Sensors
Sensors
Water heater
Furnace
Controls
Training signals

Actions performed by inhabitant specify *setpoints*

- anticipation of inhabitant desires

Gas and electricity costs

- energy conservation
An optimal control framework

Each constraint has an associated cost:

- **Discomfort cost** if inhabitant preferences are neglected
- **Energy cost** depends on device and intensity setting

The optimal control policy minimizes

$$J(t_0) = E\left[ \lim_{\kappa \to \infty} \frac{1}{\kappa} \sum_{t=t_0+1}^{t_0+\kappa} d(x_t) + e(u_t) \right]$$

where
- $t$ = index over nonoverlapping time intervals
- $t_0$ = current time interval
- $u_t$ = control decision for interval $t$
- $x_t$ = environmental state during interval $t$
ACHE
(Adaptive Control of Home Environments)

Separate control system for each task

- Air temperature regulation
  - furnace
  - space heaters
  - fans
  - dampers
  - blinds

- Lighting regulation
  - wall sconces
  - overhead lights

- Water temperature regulation
  - hot water heater

Diagram:
- ACHE
- Environmental state
- Inhabitant actions and energy costs
- Device setpoints
General architecture of ACHE

- `device regulator`
- `setpoint generator`
- `predictors`
- `state transformation`
- `occupancy model`
- `decision`
- `setpoint profile`
- `future state information`
- `state representation`
- `occupied zones`
- `instantaneous environmental state`
Knowledge encapsulation

- **device regulator**
- **setpoint generator**
- **predictors**
- **occupancy model**
- **state transformation**

Instantaneous environmental state

Decision

Knowledge about energy devices and physical layout of house

Knowledge about inhabitants’ comfort needs and preferences

Knowledge about inhabitants’ schedules
Training procedures

- System identification using neural networks
- Reinforcement learning with look-up tables or memory-based approaches
- Neural networks trained with self-supervised learning

Decision

Device regulator

Setpoint generator

Predictors

State transformation

Occupancy model

Instantaneous environmental state
Lighting control

What makes lighting control a challenge?

Twenty-two banks of lights, each with 16 intensity levels; seven banks of lights in great room alone

Motion-triggered lighting does not work

Lighting moods

Two constraints must be satisfied simultaneously
• maintaining lighting according to inhabitant preferences
• conserving energy

Range of time scales involved

Sluggishness of system
Sequential decision problem

To learn, must determine which decisions are responsible for observed costs (*temporal credit assignment*).

**Time scale dilemma**

Control decisions must be responsive to changing environmental conditions.

Therefore, time intervals must be brief (~200 ms).

But shorter time intervals make learning more difficult.
Resolving the time scale dilemma

Event-based segmentation

Detect salient events such as zone entry, change in outdoor light level. Window of time between events treated as basic interval. Lighting control decision made when event occurs.

Temporal credit assignment problem greatly simplified.

Motivated by orienting response in biological systems.
Resolving the sluggishness dilemma

*Anticipator*: Neural network that predicts which zone(s) will become occupied in the next two seconds

**Input**

- 1, 3, and 6 second average of motion signals (36)
- Instantaneous and 2 second average of door status (20)
- Instantaneous, 1 second, and 3 second average of sound level (33)
- Current zone occupancy status and durations (16)
- Time of day (2)

**Output**

- $p$(*zone* $i$ becomes occupied in next 2 seconds | currently unoccupied) (8)

**Runs every 250 ms**
Training anticipator

Occupancy model provides training signal

Two types of errors

- **miss**
  - state(t – 2000 ms)
  - state(t – 1750 ms)
  - ...
  - state(t – 250 ms)
  
  zone \( i \) becomes occupied

- **false alarm**
  - state(t)
  
  zone \( i \) vacant

Training procedure

Given partially trained net, collect misses and false alarms.
Retrain net when 200 additional examples collected.
TD algorithm for misses

![Graph showing hit/(miss+fa) vs. Number of training examples](image)
Examples of anticipator performance
Lighting controller costs

**Energy cost**
7.2 cents per kW-hr

**Discomfort cost**
1 cent per device whose level is manually adjusted

**Anticipator miss cost**
.1 cent per device that was off and should have been on

**Anticipator false alarm cost**
.1 cent per device that was turned on
Results

- about three months of data collection
- events logged only from 19:00 – 06:59
Air temperature control

- **device regulator**
- **setpoint generator**
- **predictors**
- **state transformation**
- **occupancy model**

**predictive optimal controller**
Searches over a fixed horizon of $\kappa$ decisions, $\delta$ minutes apart, for a decision sequence that minimizes expected cost.

**predicts future occupancy status of house**
Based on: time of day, day of week, average proportion of time home occupied in the 10, 20, and 30 minutes from present time of day on the previous 3 days and on the same day of the week during the past 4 weeks, proportion of time home was occupied during the past 60, 180, and 360 minutes

**performs first decision in sequence**

**reports house occupancy**
To estimate misery, must predict future house occupancy and indoor temperature.

\[ \tilde{m}_u(x_t) = \tilde{m}_u[o(t), h_u(t)] \]

\[ = p\{o(t) = 0\} m[0, h_u(t)] + p\{o(t) = 1\} m[1, h_u(t)] \]

\[ m(o, h) = o \rho \sigma \frac{\delta}{24 \times 60} \frac{\max(0, |\lambda - h| - \varepsilon)^2}{25} \]

\{ economic loss model \}

\textit{salary ($/hr)} \quad \textit{productivity loss (hr)}
Simulation methodology

Simulated environment

- thermal and comfort cost models are exact
- outdoor temperature, \( g \), constant 0°C

Occupancy data

- real data collected from neural net house over an 8 month period
- artificial data, manipulating regularity of occupant schedule

Variability index = 0

Variability index = 1
Alternative heating policies

• Constant Temperature Policy
  setpoint = 22.5°C

• Occupancy Triggered Policy
  setpoint = 18°C if house empty
  22.5°C if house occupied

• Setback Thermostat Policy
  setpoint = 18°C half hour before mean morning departure time for day of week
  22.5°C half hour before mean evening return time

Each policy produces a setpoint at each time step.
Furnace turns on if actual temperature lower than setpoint.
Comparison of control policies using artificial occupancy data

Productivity Loss = 1.0 hr.

Productivity Loss = 3.0 hr.
Comparison of control policies using real occupancy data

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<th>Mean Daily Cost</th>
<th>productivity loss</th>
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Empirical issues

Are there sufficiently robust regularities in the inhabitants’ behavior that ACHE can exploit them?

Is a system of ACHE’s complexity warranted, or will a simple rule-based system do 99% of the job?