The Adaptive House

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http://www.cs.colorado.edu/~mozer/adaptive-house

Home automation

Homes might be programmed to

- close drapes at night

- turn down sterero 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 laserdiscs 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*)

André Malepart of Honeywell visits Hank and Darlene Johnson regularly to "fine tune" their home automation system.

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.
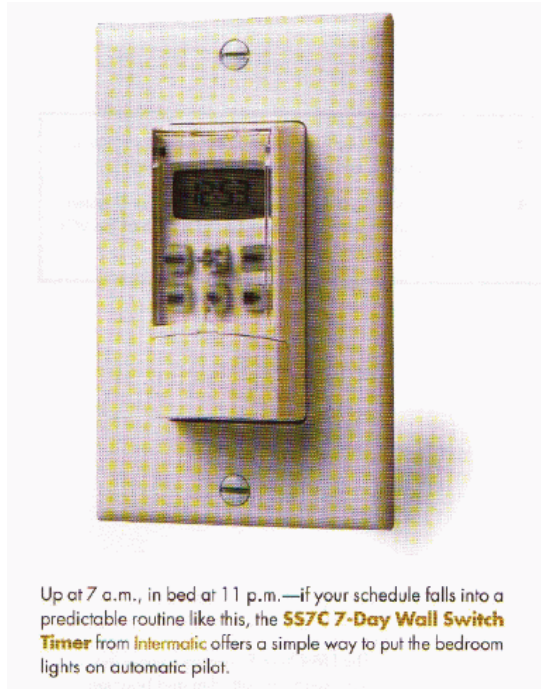
"I use about half of it," said Becker...

### 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 meatballs. 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.
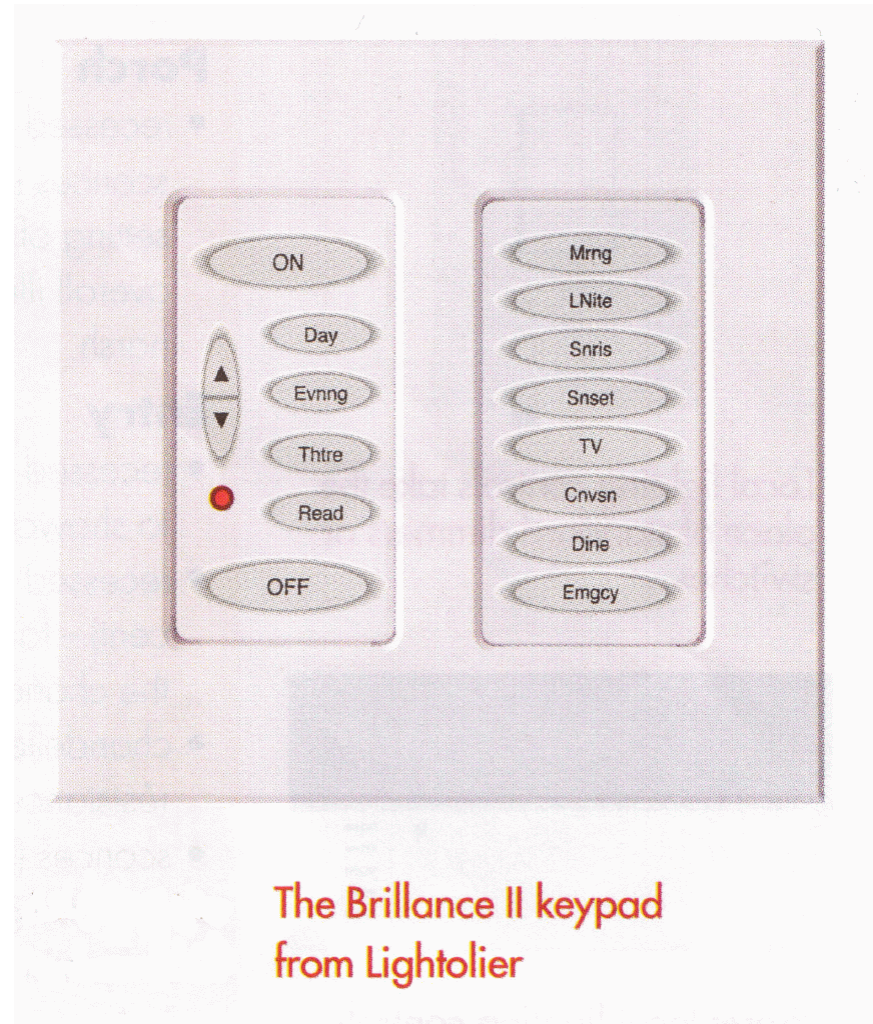
The Brillance II keypad
from Lightolier

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

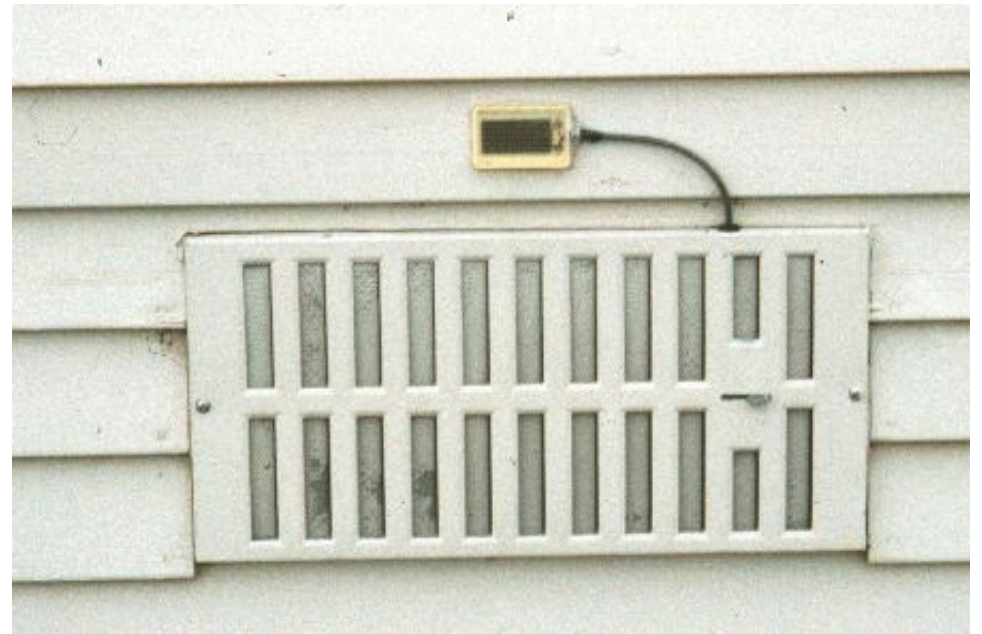## Residence in Marshall, Colorado, outside of Boulder
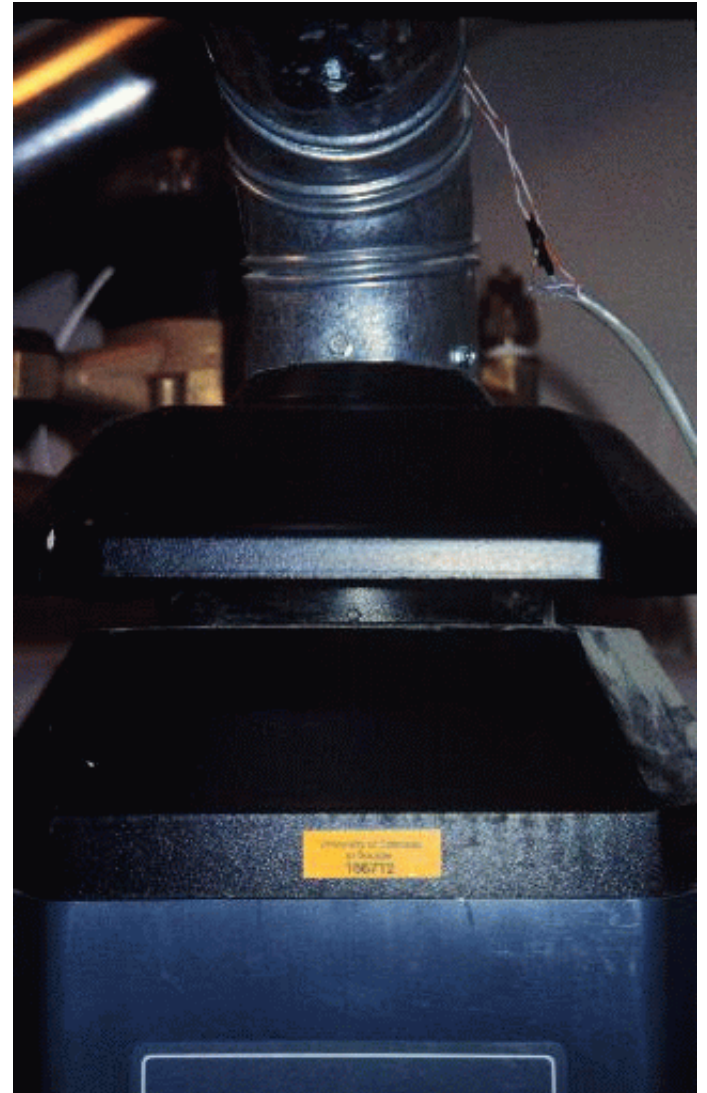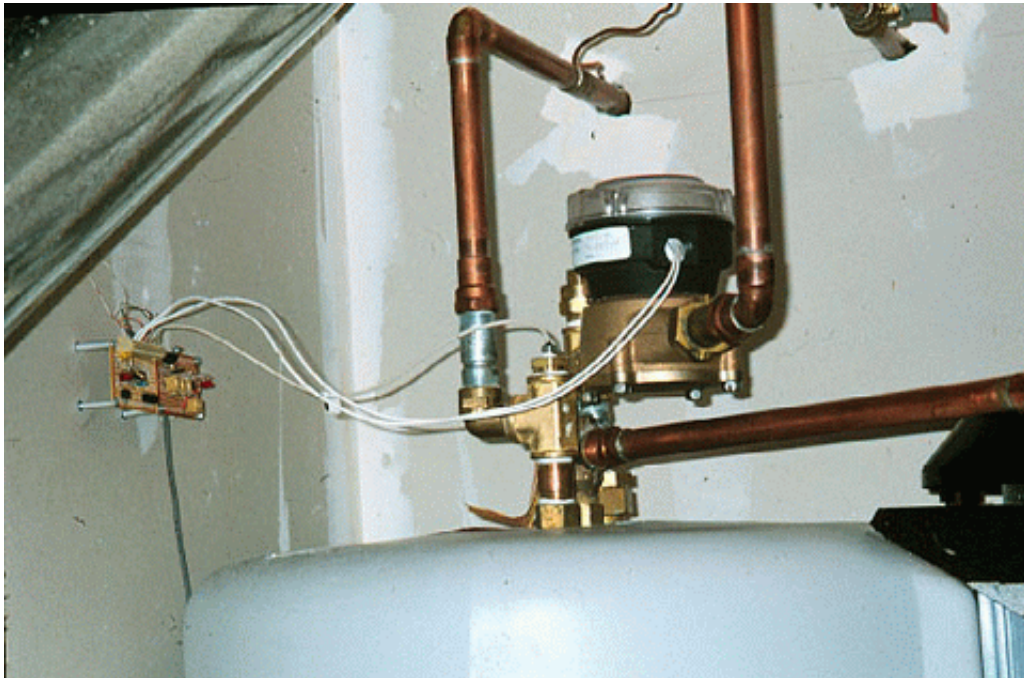
Some of the gang

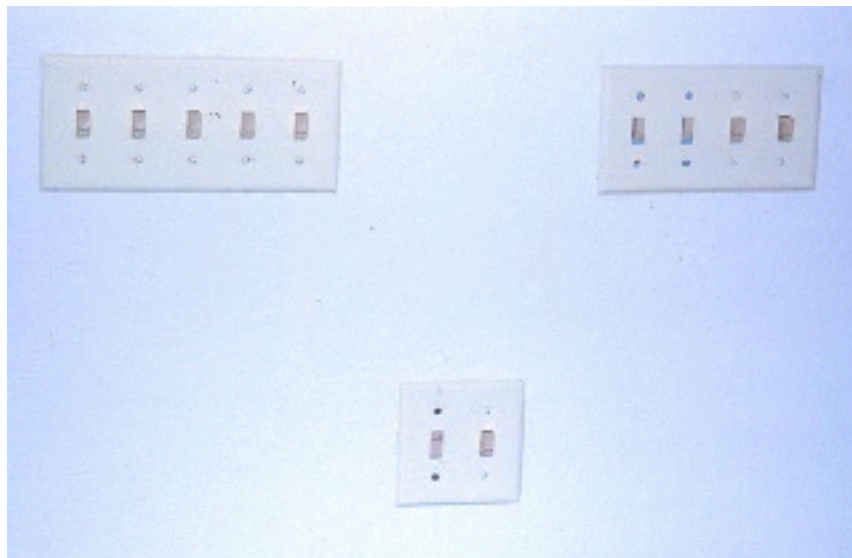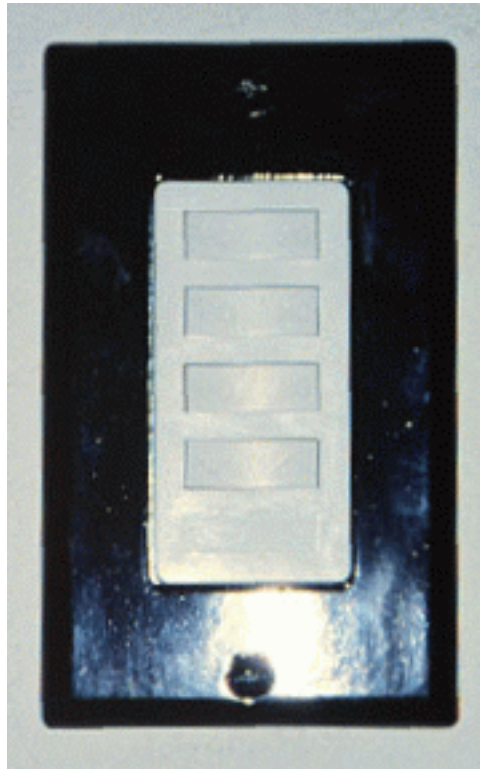# Great room

Bedrooms and bathrooms

Sensors

Sensors

Water heater

Furnace

Controls

Computers

Floor plan

Great Room

Kitchen

Bath 3

Bedroom 3

Entry

Master Bedroom

Master Bath

Bath 2

Bedroom 2

Garage
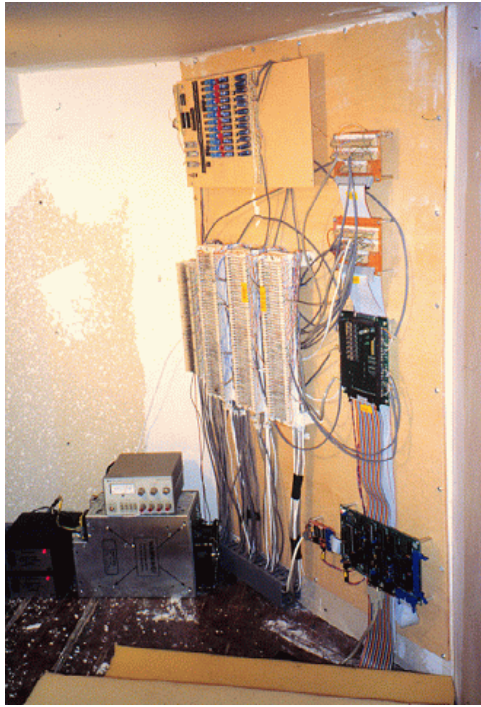
Training signals

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

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

where t = index over nonoverlapping time intervals
t_0 = current time interval
$\mathbf{u}_t$ = control decision for interval t
$\mathbf{x}_t$ = environmental state during interval t

ACHE
(**A**daptive **C**ontrol of **H**ome **E**nvironments)

Separate control system for each task

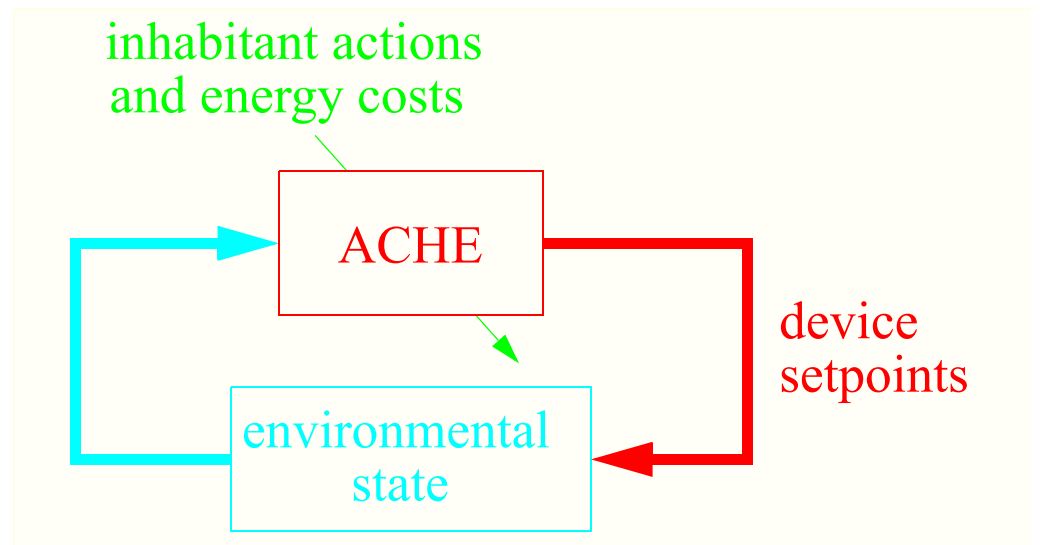air temperature regulation

  furnace
  space heaters
  fans
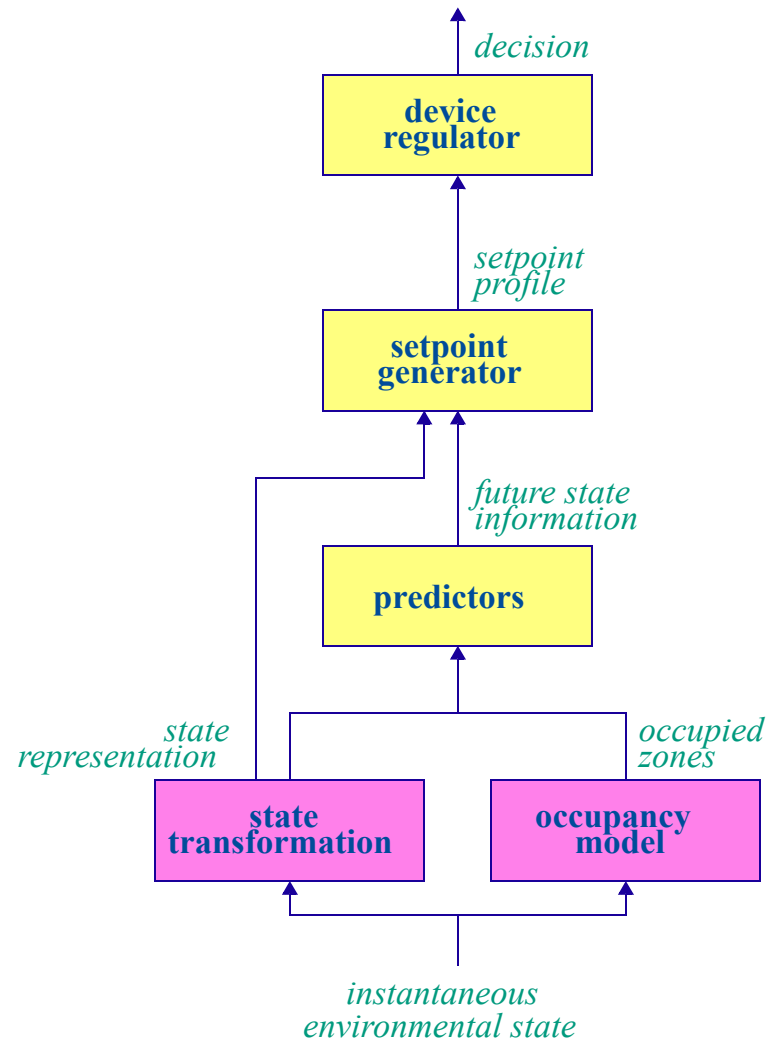 dampers
  blinds

lighting regulation

  wall sconces
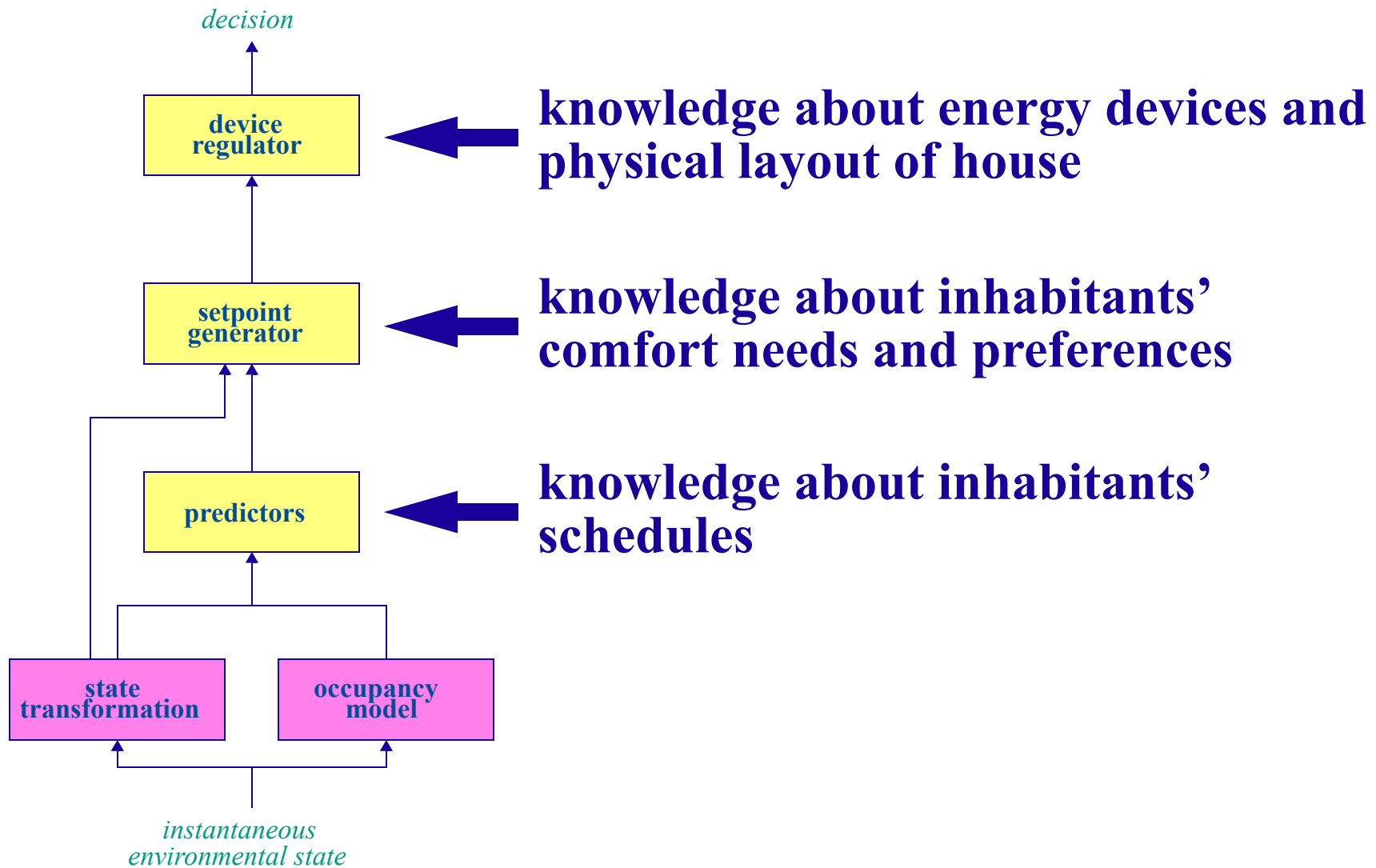 overhead lights

water temperature regulation

  hot water heater
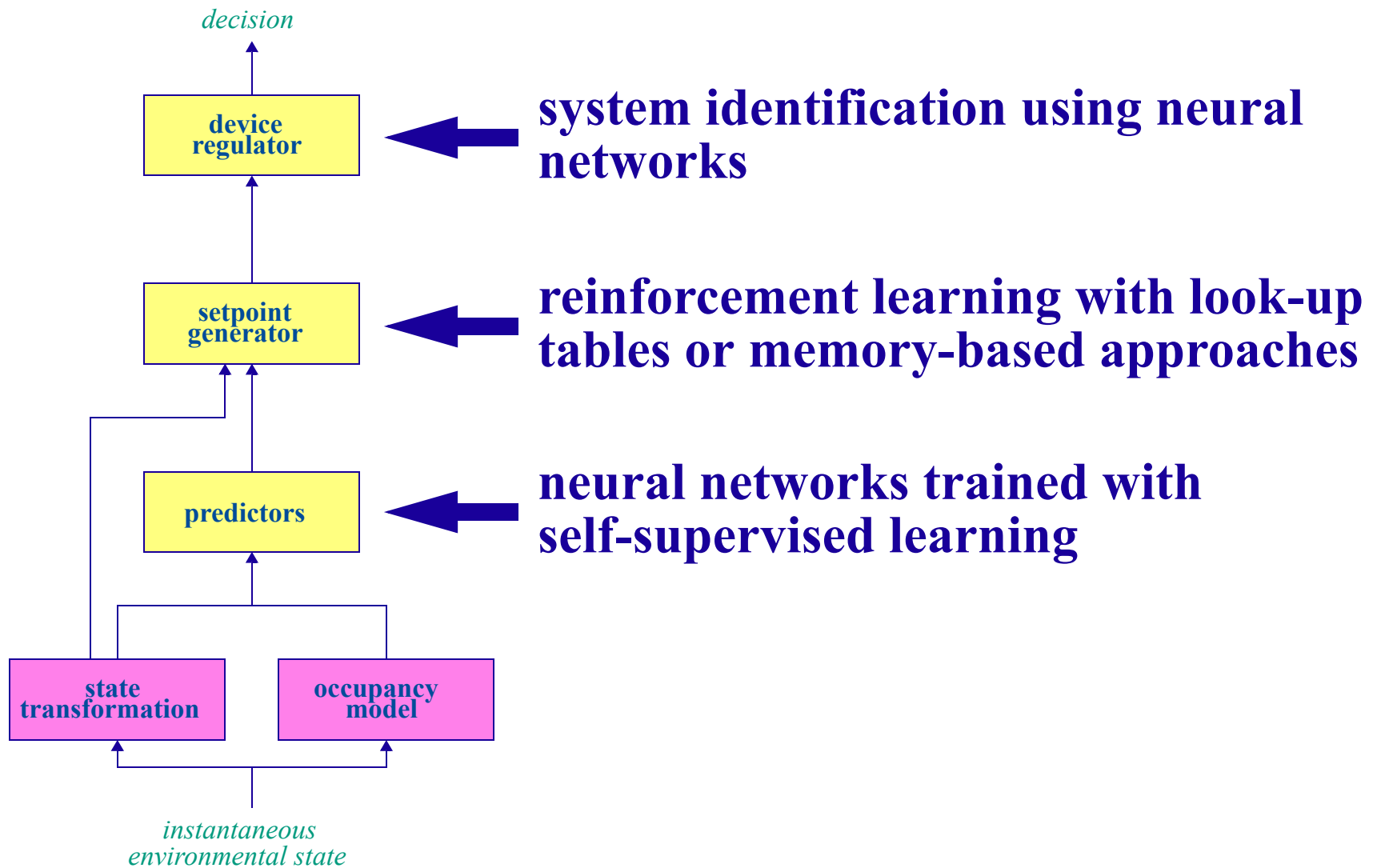
inhabitant actions
and energy costs

ACHE

device
setpoints

environmental
state

General architecture of ACHE

Knowledge encapsulation

decision

device regulator ← **knowledge about energy devices and physical layout of house**

setpoint generator ← **knowledge about inhabitants' comfort needs and preferences**

predictors ← **knowledge about inhabitants' schedules**

state transformation   **occupancy model**

instantaneous environmental state

Training procedures

decision

device regulator ← **system identification using neural networks**

setpoint generator ← **reinforcement learning with look-up tables or memory-based approaches**

predictors ← **neural networks trained with self-supervised learning**

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
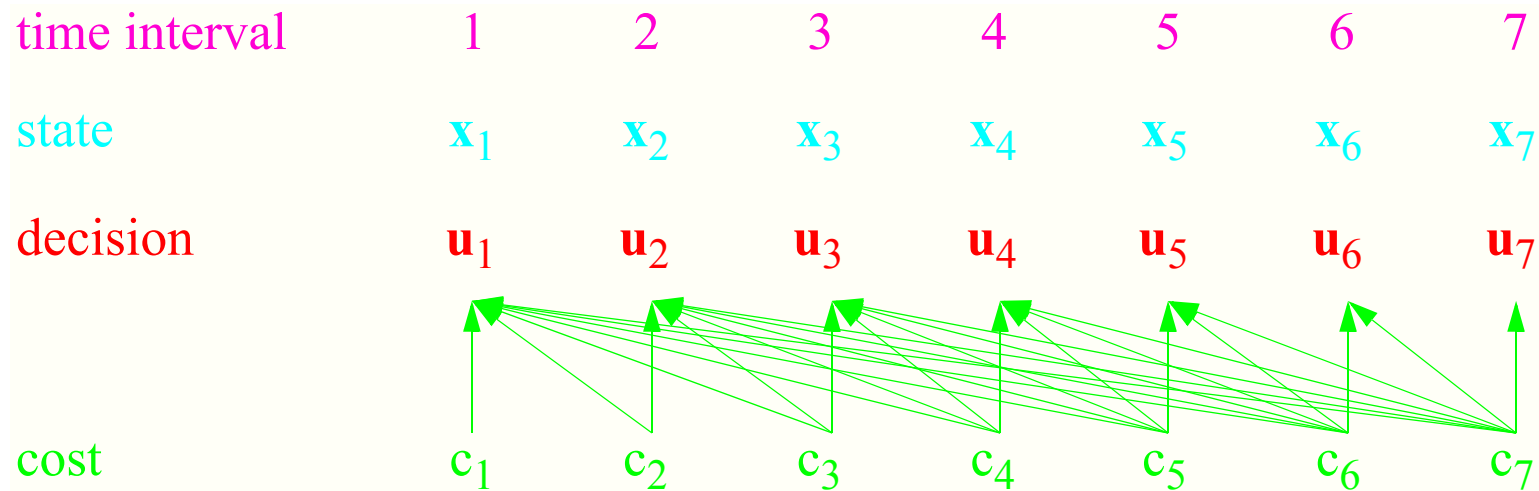
Lighting moods

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

time interval	1	2	3	4	5	6	7
state	x_1	x_2	x_3	x_4	x_5	x_6	x_7
decision	u_1	u_2	u_3	u_4	u_5	u_6	u_7
cost	c_1	c_2	c_3	c_4	c_5	c_6	c_7

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.
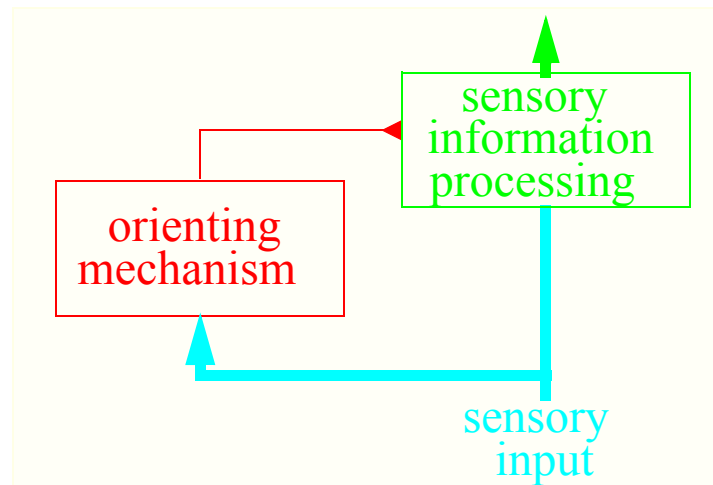
Resolving the time scale dilemma

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)
                    ...   zone i becomes occupied
                    state(t – 250 ms)
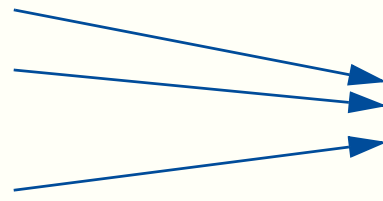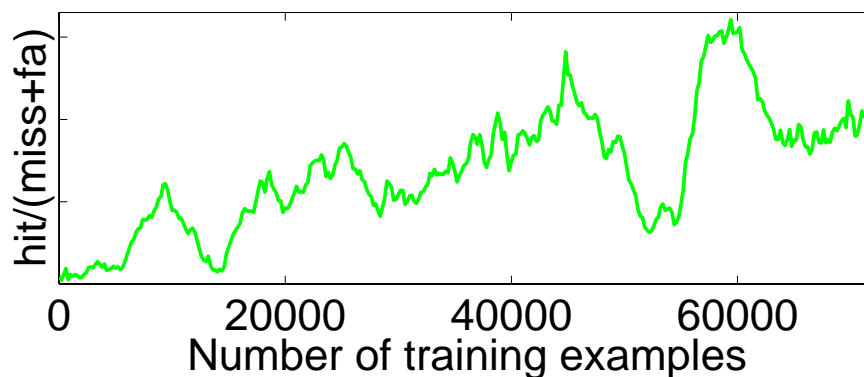
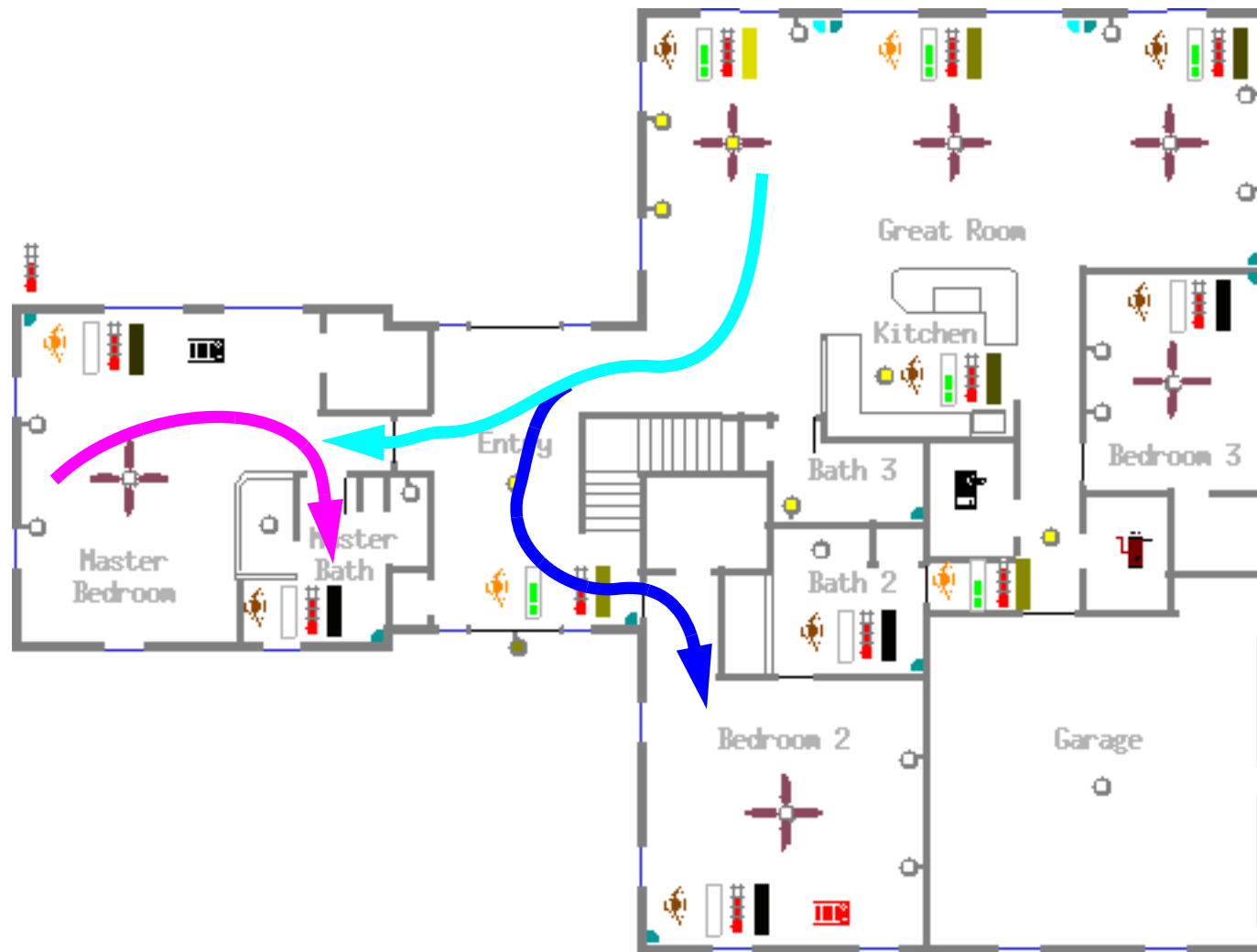false alarm   state(t)   zone i vacant

Training procedure

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

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
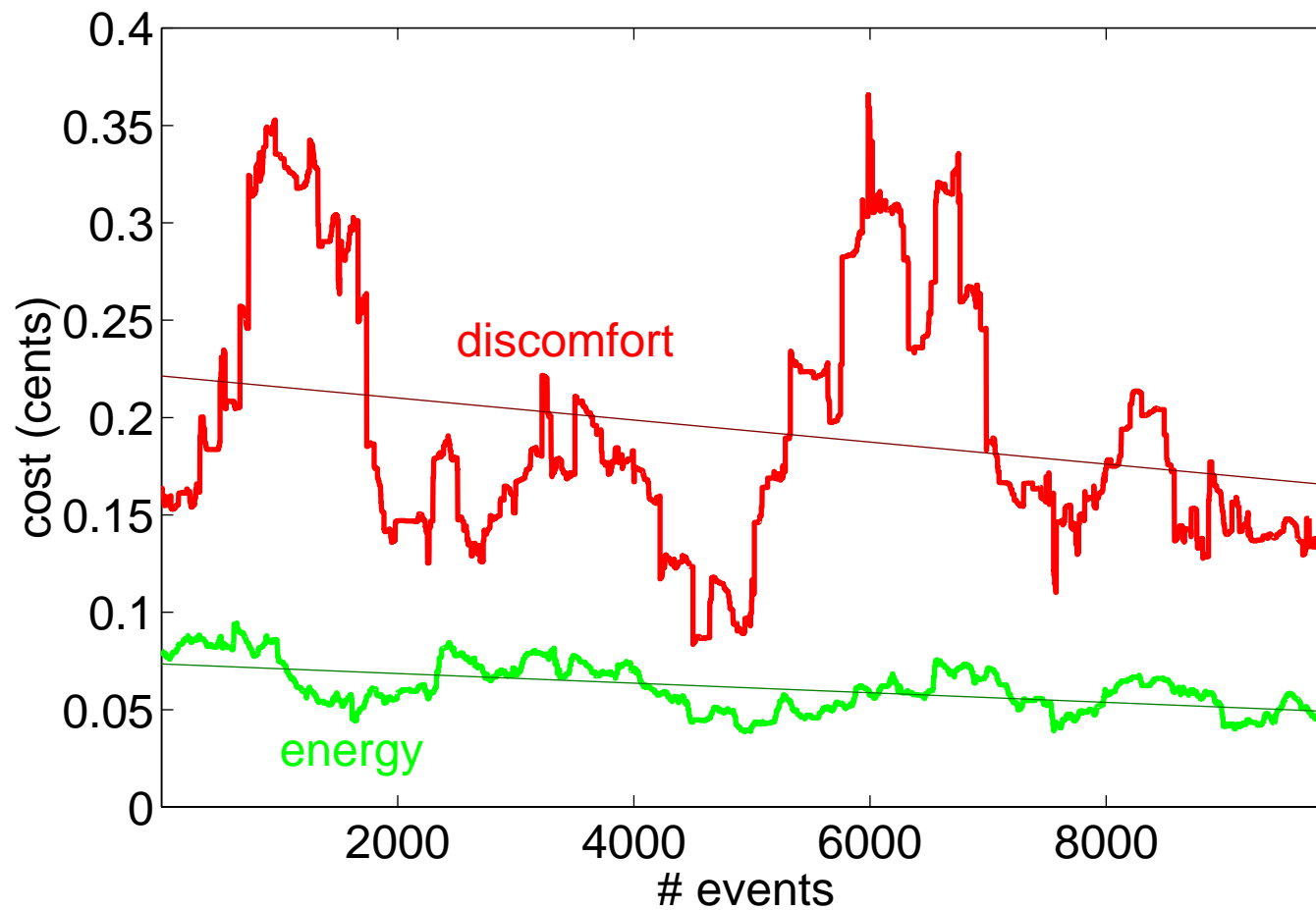
Anticipator miss cost

.1 cent per device that was off and should have been on
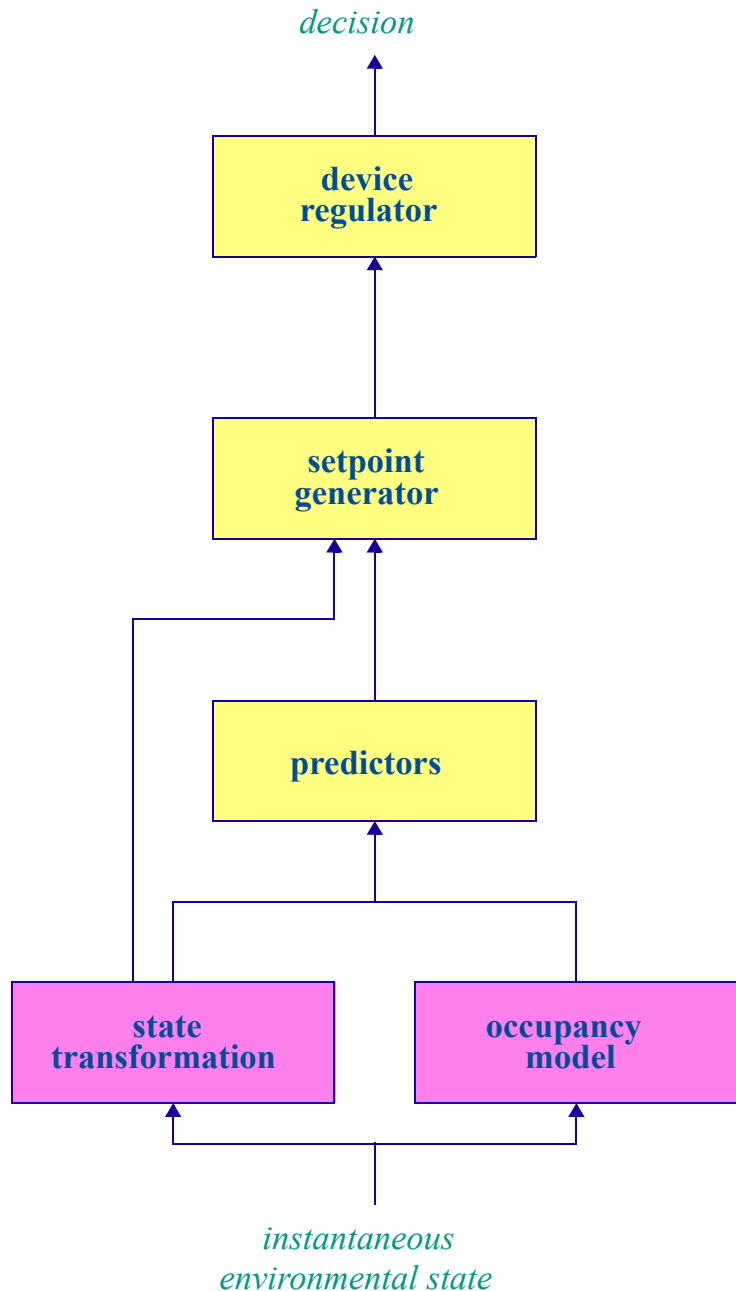
Anticipator false alarm cost

.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

decision

device regulator — **performs first decision in sequence**

setpoint generator — **predictive optimal controller**
Searches over a fixed horizon of κ decisions, δ minutes apart, for a decision sequence that minimizes expected cost.

predictors — **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

state transformation

occupancy model — **reports house occupancy**

instantaneous environmental state

Misery cost

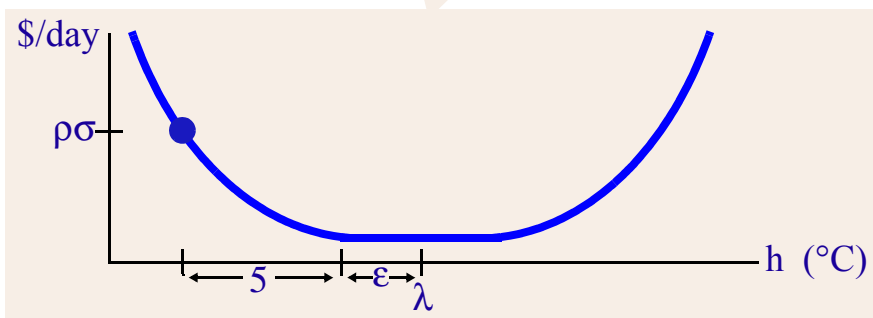*expected misery cost for decision sequence* **u**   *occupancy status*   *indoor air temperature*

$$\overline{m}_{\mathbf{u}}(\mathbf{x}_t) = \overline{m}_{\mathbf{u}}[o(t), h_{\mathbf{u}}(t)]$$

$$= p\{o(t) = 0\}\, m[0, h_{\mathbf{u}}(t)] + p\{o(t) = 1\}\, m[1, h_{\mathbf{u}}(t)]$$

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

salary ($/hr)   } *economic loss model*
productivity loss (hr)

$/day

$\rho\sigma$

$\longleftarrow 5 \longrightarrow \;\; \longleftarrow\varepsilon\longrightarrow$
λ

h (°C)

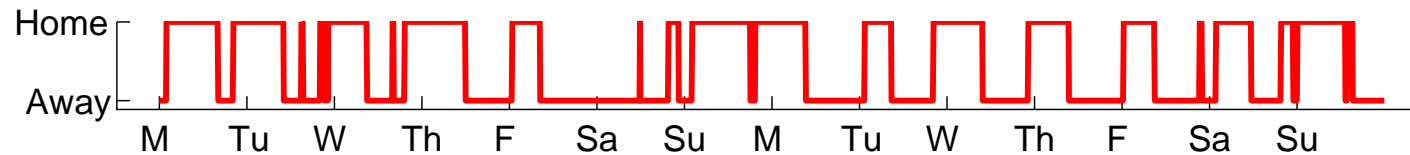**To estimate misery, must predict future *house occupancy* and *indoor temperature*.**

Simulation methodology
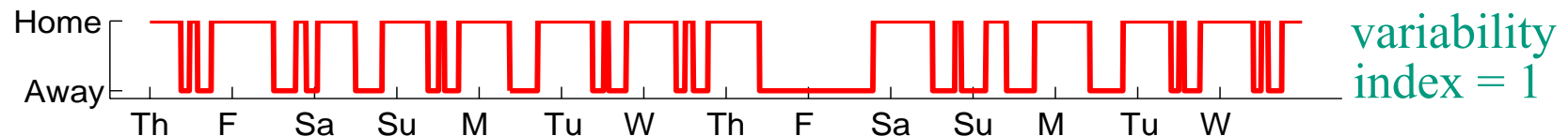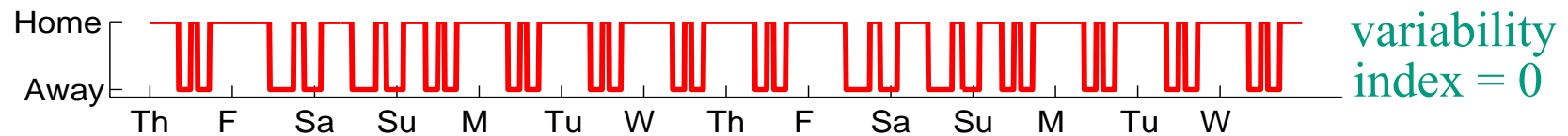
Simulated environment

- 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

Alternative heating policies

- **Constant Temperature Policy**

  setpoint = 22.5°C

- **Occupancy Triggered Policy**

  setpoint = 18°C if house empty
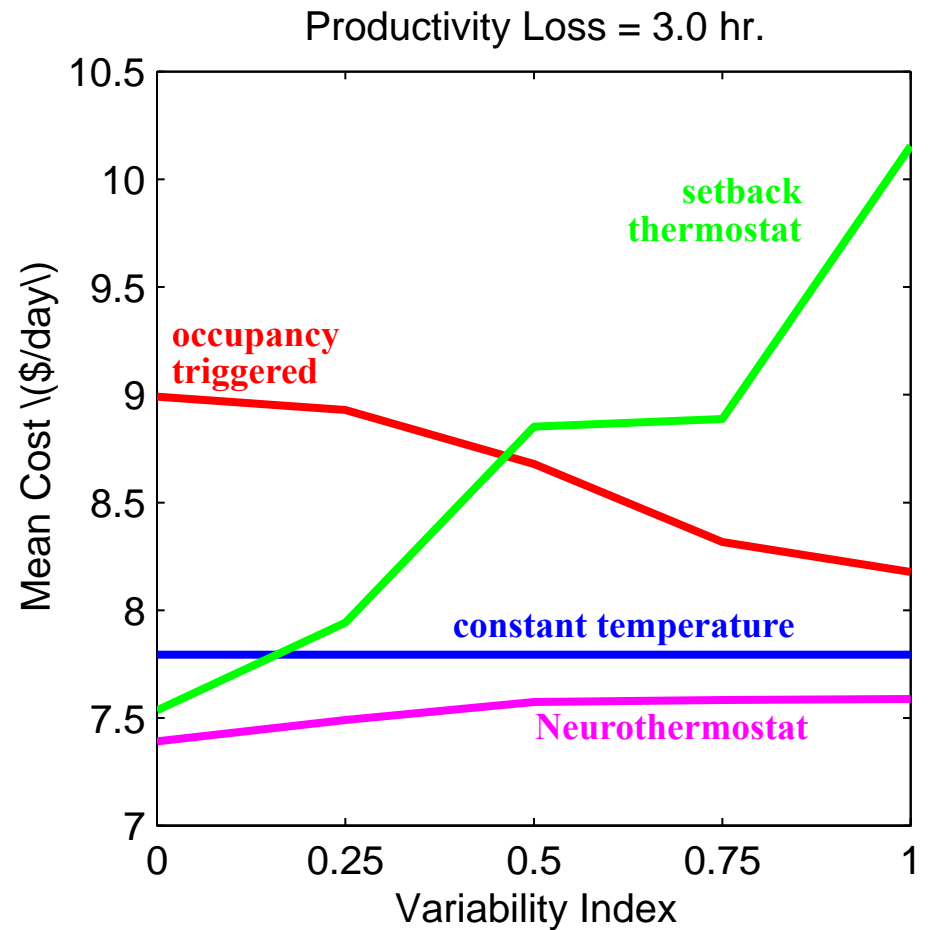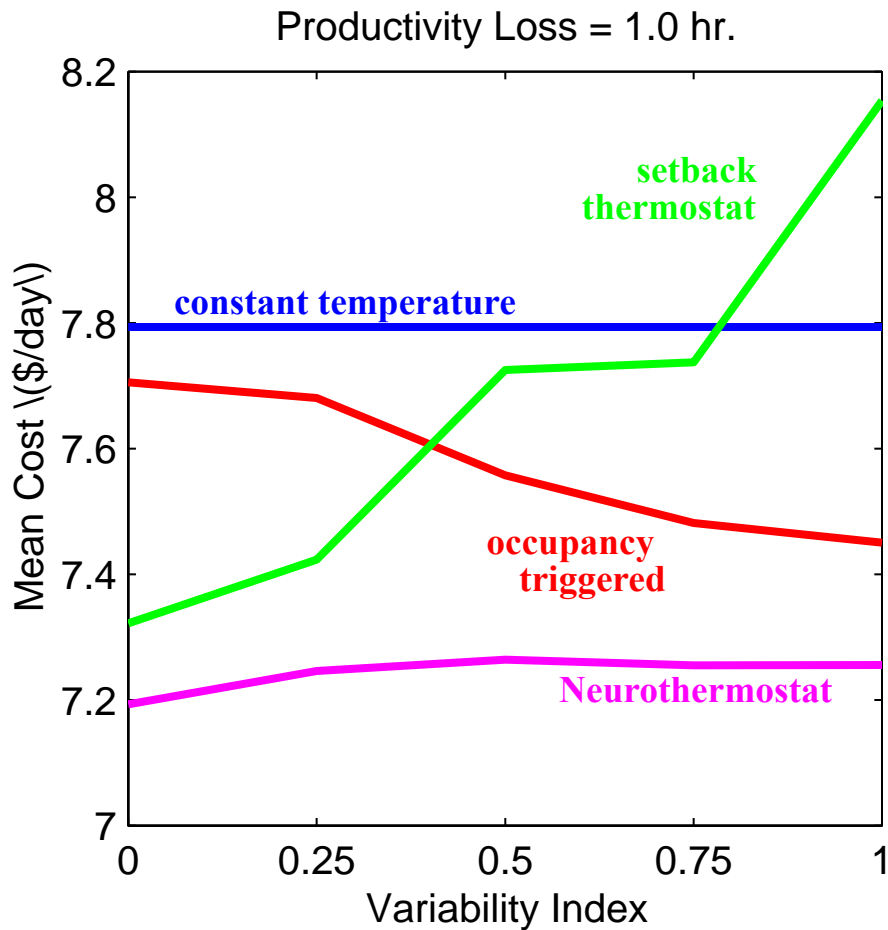 22.5°C if house occupied

- **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.

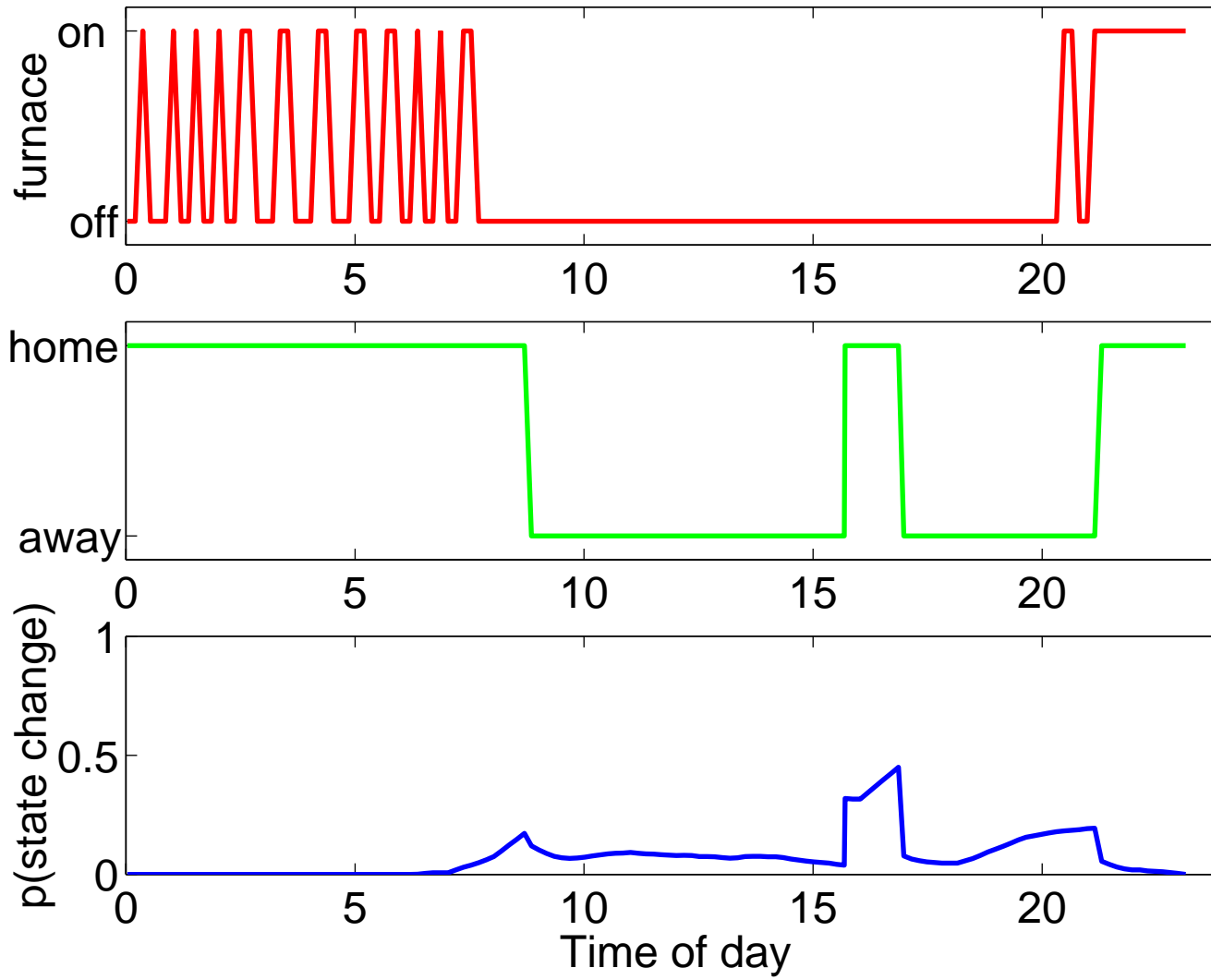Comparison of control policies using artificial occupancy data

Comparison of control policies using real occupancy data

Mean Daily Cost

	productivity loss	
	$\rho = 1$	$\rho = 3$
Neurothermostat	$6.77	$7.05
constant temperature	$7.85	$7.85
occupancy triggered	$7.49	$8.66
setback thermostat	$8.12	$9.74

Sample Performance

Sunday March 6, 2000

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?