Developing synergies for automated optimal control of residential heat pumps

Hussain Kazmi, Farah Cheaib, Johan Driesen

ELECTA, ESAT, KU Leuven, Belgium

Enervalis, Belgium
Research question

Is it possible to improve heat pump efficiency in real world NZEBs?

Constraints

No prior system information
Only standard sensor data
Overview of savings

DHW Control using ASHPs for recently refurbished NZEBs in The Netherlands

Time frame: 3 weeks

~ 19 houses with energy efficiency algorithm
~ 13 houses with default controller

Choose 10 houses with the most similar water demand

Observed

Relative energy savings: 31%
Absolute energy savings: 124 kWh

Projected

Annual energy savings: ~215 kWh/h
Annual monetary savings: ~50 Eur/h

No comfort violations recorded in 3 weeks
General workflow

1. Initialize MDP, $M \leftarrow (X, U, T, R)$, $\pi \leftarrow \pi_{default}$
2. Repeat forever:
   
   (a) Update experiences: $x_t, u_t, r_{t+1}, x_{t+1}, \ldots$
   (b) Update the transition function, $T : X \times U \times X \rightarrow \mathbb{R}^2$
   (c) Update the reward function, $R : X \times U \times X \rightarrow \mathbb{R}^2$
   (d) Predict $O$, the occupant behaviour
   (e) Predict $T_a$, the ambient temperature
   (f) Simulate possible future scenarios, given $x_t$
   (g) Update $\pi \leftarrow \text{argmax}_{u} (\mathbb{E}[r + \epsilon]_t)$
   (h) Execute $\pi$

**Definition of the MDP**

State $(X)$ refers to current temperature in the building or storage vessel
Action $(U)$ refers to the controller of the heat pump (e.g. on/off or power etc.)
Transition $(T)$ function refers to temperature in the building or storage vessel
Reward $(R)$ function refers to the energy consumed by the heat pump
Learnt model – storage vessel

Vessel model learnt and associated uncertainty – states previously ‘seen’ have low uncertainty while unseen states are more uncertain

Vessel temperature @ mid point, observation and prediction with uncertainty bands

Learnt model uncertainty decreases over time
Learnt model – heat pump (DHW)

Error is distributed normally with a low standard deviation
Learnt model – building thermal inertia

Learnt temperature behaviour in house 1

Learnt temperature behaviour in house 2

The average error is low but the spread is fairly large, caused by unexplained anomalies in sensor data.
Learnt model – heat pump (SH)

Error is distributed normally but is strongly dependent on household behaviour
Optimizing for energy efficiency - DHW

Simulation results

Actual results
Data collected for 3 weeks over 13 houses
Conclusions

• **Generalizable savings of > 20% possible**
• Sweet spot for optimization
  • Daily DHW consumption <= vessel capacity / 2
• Energy efficiency gains possible by leveraging human behaviour
• Little human intervention required at runtime
Extensions

• Maximizing solar self consumption
• Maximizing occupant comfort
• Minimizing economic costs (e.g. dual pricing etc.)
• Providing ancillary services
  • DSO use case (e.g. peak shaving)
  • TSO use case (e.g. frequency regulation / reserve)
Thank you!

• Questions?
  • Hussain.kazmi@Enervalis.com
Default behaviour

\[ u_t = \begin{cases} 
1, & \text{if } T_s < T_{th} \\
0, & \text{if } T_s \geq T_{th} 
\end{cases} \]

Reheat cycle is triggered as soon as temperature drops below threshold.
Heuristic optimization

\[ u_t = \begin{cases} 
1, & \text{if } T_S < T_{th} \\
0, & \text{if } T_S \geq T_{th} 
\end{cases} \]

Reheat cycle is triggered as soon as temperature drops below threshold

\[ u_t = \begin{cases} 
1, & \text{if } HW_{(v,t)} < \sum_{k=i}^{i+n} HW_{(p,k)} \\
0, & \text{if } HW_{(v,t)} \geq \sum_{k=i}^{i+n} HW_{(p,k)} 
\end{cases} \]

Reheat cycle is triggered once estimated remaining hot water is less than predicted occupant demand
Other factors

Other factors influencing heat pump efficiency
1. Ambient temperature
2. Water temperature at the reheat circuit
3. Global vs. local optima (need for search)