Robust Scheduling of Residential DER Using a Novel Energy Service Decision-Support Tool

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1 Background

- Energy services are energy forms and processes from where consumers derive the value of energy carriers like electricity and gas
- Examples of energy services are space heating and cooling, water heating, illumination, information processing and communications, and entertainment
- The provision of energy services may be improved by facilitating larger roles for distributed energy resources (DER)
- Robust DER schedules should be formulated due to stochastic energy service demand and energy prices, and availability of some DER.

2 Our 3-Step Solution

Step 1: Use an energy service model that
- assigns benefit to the energy that realizes the service
- models temporal changes to demand and benefit

Step 2: Create an optimal scenario tree that would represent the range of uncertainty. The tree is constructed using random sampling followed by backward scenario reduction.

Step 3: Schedule the operation of DER to maximize the expected net benefit over the optimal scenario tree.

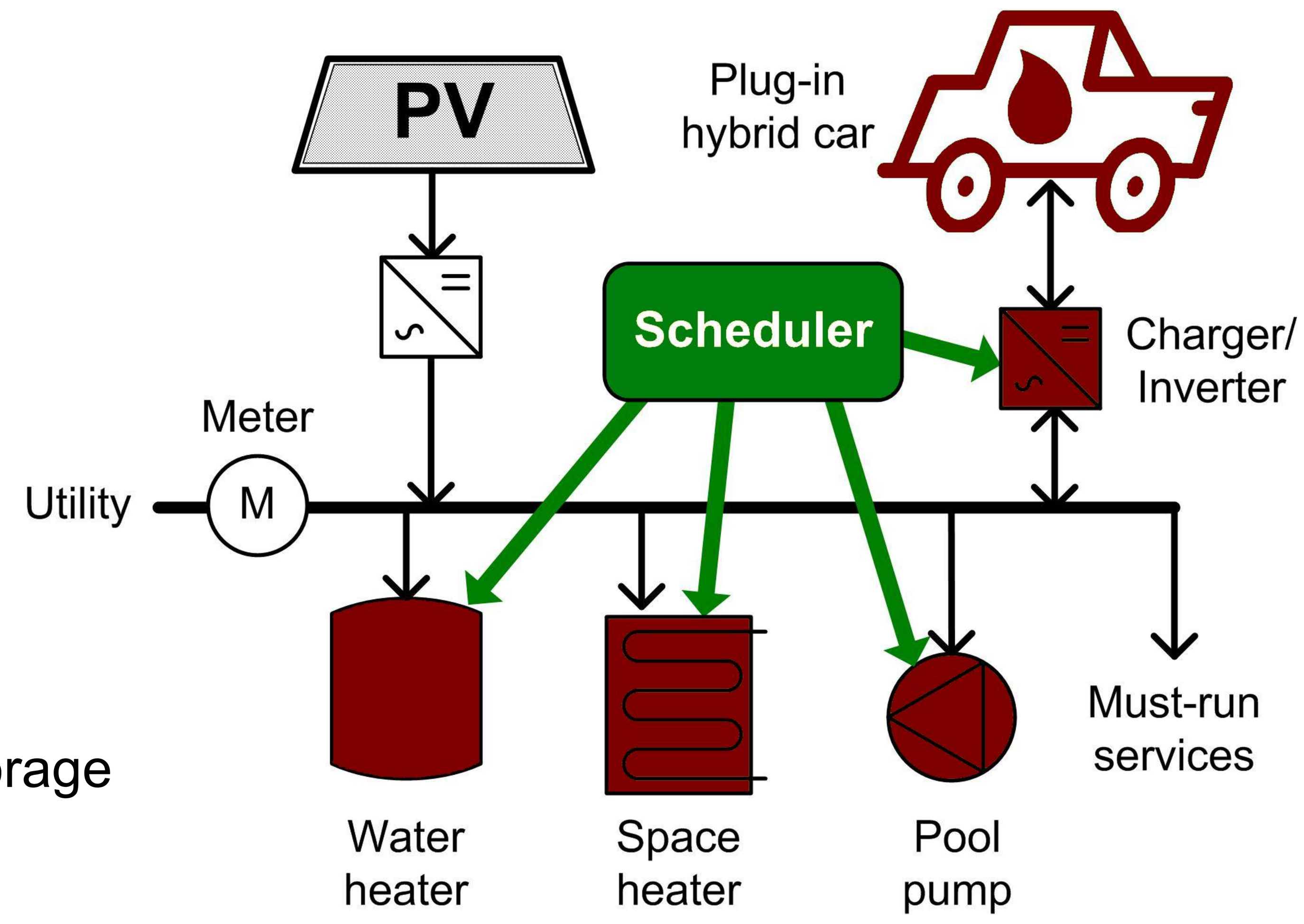
Net benefit = benefit from services – cost of energy service provision = f_0

$$\min \mathrm{E}\{f_0(x,a)\} = \min \Sigma\, \pi(a_i) f_0(x,a_i),\ \Sigma\, \pi(a_i) = 1$$

3 Smart Home Case Study

Services to provide
- Space heating
- Hot water
- PHEV battery charging
- Pool pumping
- Must-run services (food storage and preparation, illumination, etc.)

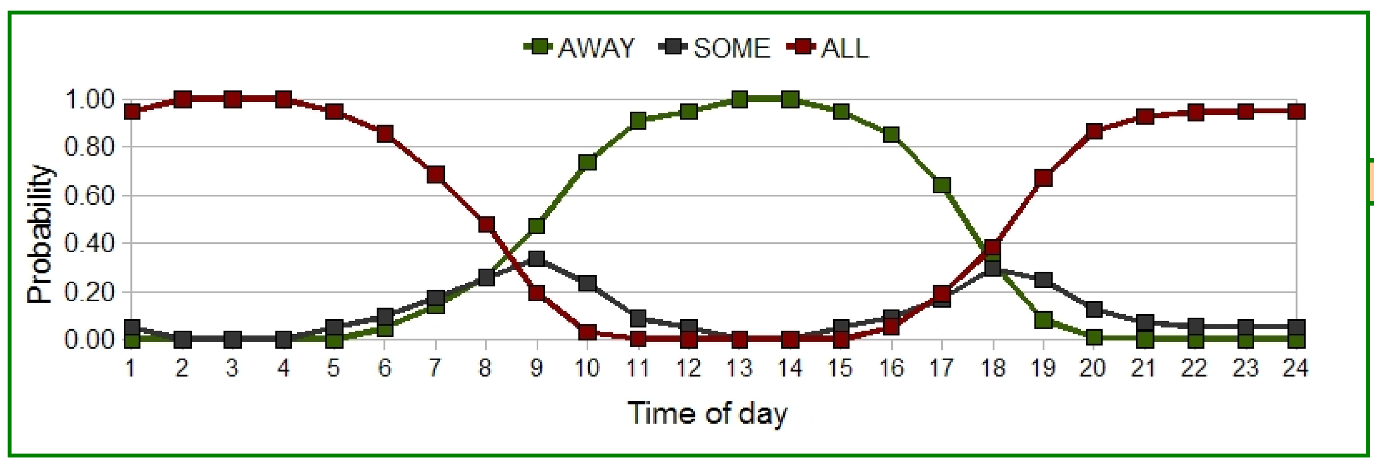
Stochastic variables
- Demand for energy services
- Availability of PHEV as energy storage
- Status of DPP



Scenario A: DPP will not be active
Scenario B: PHEV is available as storage but DPP has varying forecast probability
Scenario C: The residents are unsure of DPP status and PHEV availability

The robust schedule is compared against the schedules derived
- when all residents are at home all day
- using the most likely occupancy

4 The Models and Scheduler at Work



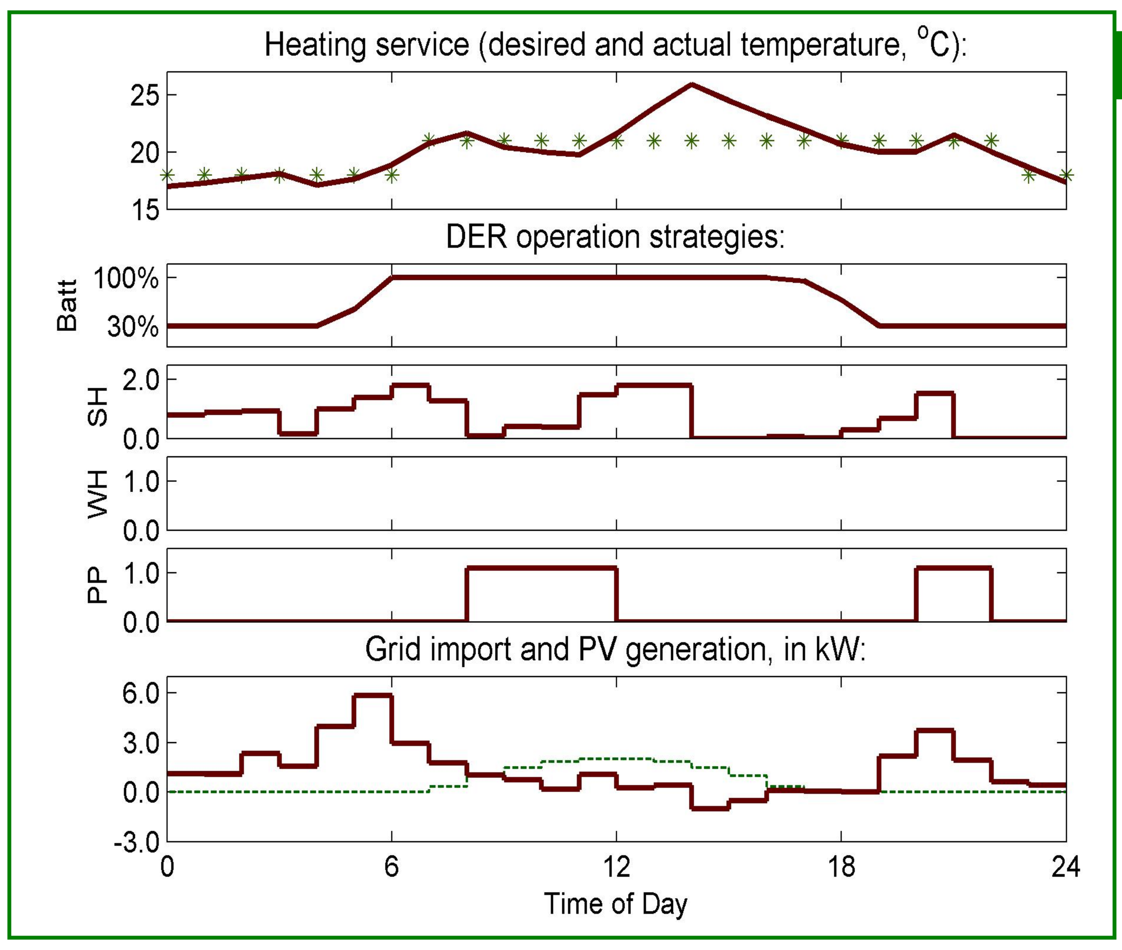
Occupancy model: Time-inhomogeneous Markov process

Forecasts: Probability that
1. DPP is active
2. PHEV is available as storage DER

Random sampling → Backward scenario reduction → Optimal scenario tree → Map each scenario to energy service demand → DER Scheduler → Operation Schedule

Scenario ID	Probability (%)	Hourly Occupancy*	a_P	a_D
a_{r1}	10.2		1	0
a_{r2}	7.4		1	0
a_{r3}	7.2		1	0
a_{r4}	6.8		1	0
a_{r5}	6.6		1	0
a_{r6}	6.1		1	0
a_{r7}	5.8		1	0
a_{r8}	5.2		1	0
a_{r9}	5.1		1	0
a_{r10}	4.7		1	0
a_{r11}	4.7		1	0
a_{r12}	4.3		1	0
a_{r13}	4.3		1	0
a_{r14}	3.6		1	0
a_{r15}	3.5		1	0
a_{r16}	3.2		1	0
a_{r17}	3.2		1	0
a_{r18}	3.1		1	0
a_{r19}	2.9		1	0
a_{r20}	2.3		1	0

DER and building characteristics, weather, and electricity rates



5 Conclusions

This research work demonstrates that robust day-ahead DER operation schedules may be generated using the novel decision-support tool by formulating a stochastic programming problem for the DER scheduler.

While practical implementation may be some way off, the work highlights the potential value of focusing on robust automated scheduling of DER in future ‘smart’ homes where there will be considerable uncertainties to manage.