

A Realistic Dataset for the Smart Home Device Scheduling Problem for DCOPs

William Kluegel¹, Muhammad Iqbal¹,

Ferdinando Fioretto²,

William Yeoh¹, Enrico Pontelli¹

¹New Mexico State University

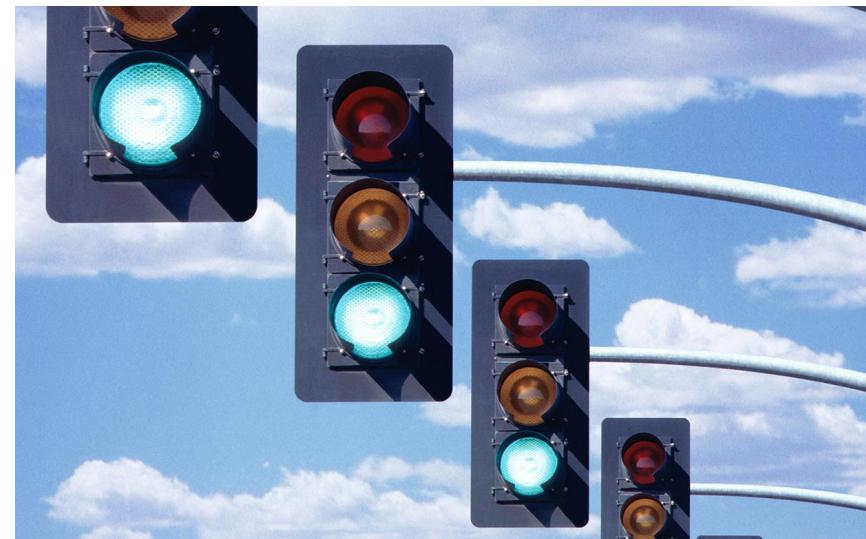
²University of Michigan

May, 2017

Outline

- DCOPs and the need for test cases
- Smart Homes Device Scheduling (SHDS)
- SHDS dataset
- Spam

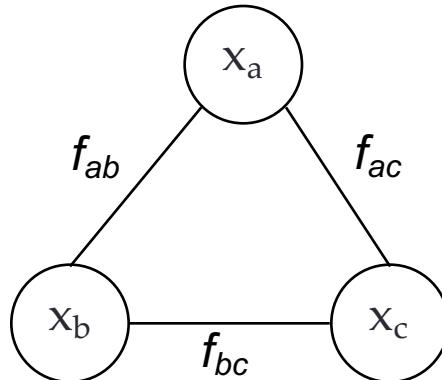
Distributed Constraint Optimization



Distributed Constraint Optimization

$\langle \mathcal{X}, \mathcal{D}, \mathcal{F}, \mathcal{A}, \alpha \rangle$:

- \mathcal{X} : Set of variables.
- \mathcal{D} : Set of finite domains for each variable.
- \mathcal{F} : Set of constraints between variables.
- \mathcal{A} : Set of agents, controlling the variables in \mathcal{X} .
- α : Mapping of variables to agents.



Constraint graph

x_a	x_b	cost
0	0	3
0	1	∞
1	0	2
1	1	5

Constraint (cost table)

Distributed Constraint Optimization

$\langle \mathcal{X}, \mathcal{D}, \mathcal{F}, \mathcal{A}, \alpha \rangle$:

- \mathcal{X} : Set of variables.
- \mathcal{D} : Set of finite domains for each variable.
- \mathcal{F} : Set of constraints between variables.
- \mathcal{A} : Set of agents, controlling the variables in \mathcal{X} .
- α : Mapping of variables to agents.
- **GOAL**: Find a cost minimal assignment.

$$\begin{aligned}\mathbf{x}^* &= \arg \min_{\mathbf{x}} \mathbf{F}(\mathbf{x}) \\ &= \arg \min_{\mathbf{x}} \sum_{f \in \mathcal{F}} f(\mathbf{x}|_{\text{scope}(f)})\end{aligned}$$

DCOP: Assumptions

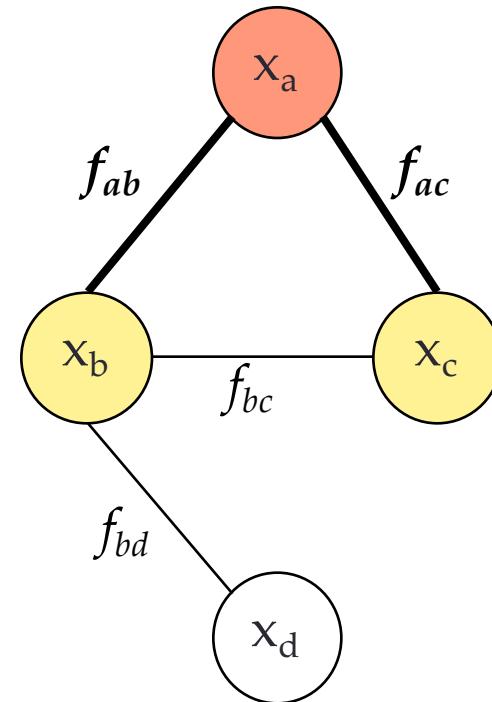
- Agents coordinate an assignment for their variables.
- Agents operate distributedly.

Communication:

- By exchanging messages.
- Restricted to agent's local neighbors.

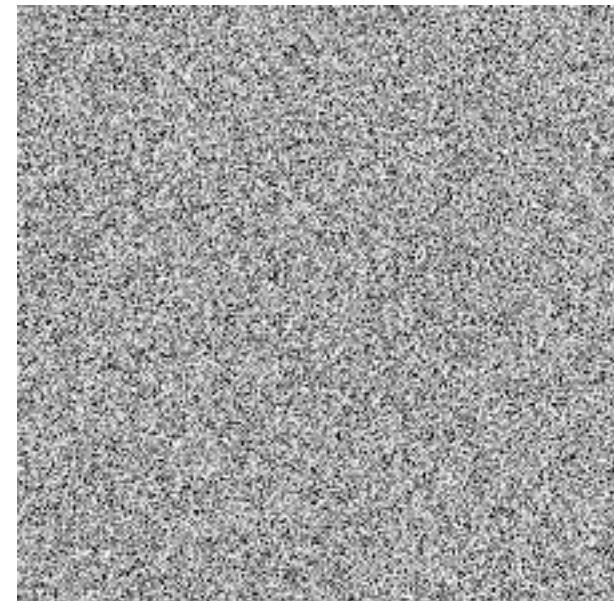
Knowledge:

- Restricted to agent's sub-problem.



DCOP: Evaluation

- **Metrics**
 - Network load
 - Runtime (or NCCCs)
 - Solution quality
- **Domains:**
 - Mostly random problems
- **Simplifying assumptions**
 - Single variable per agent
 - Binary constraints
- Not consistent with many (more) realistic applications



Home Automation

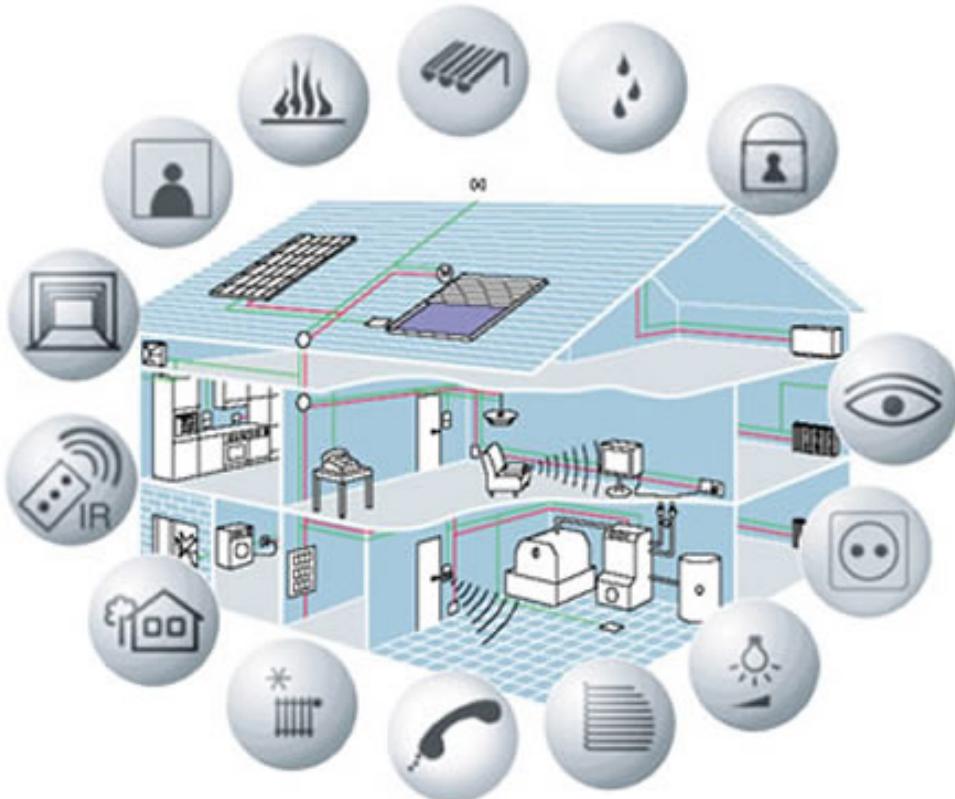


Fig.1



Fig.2

Network of smart homes

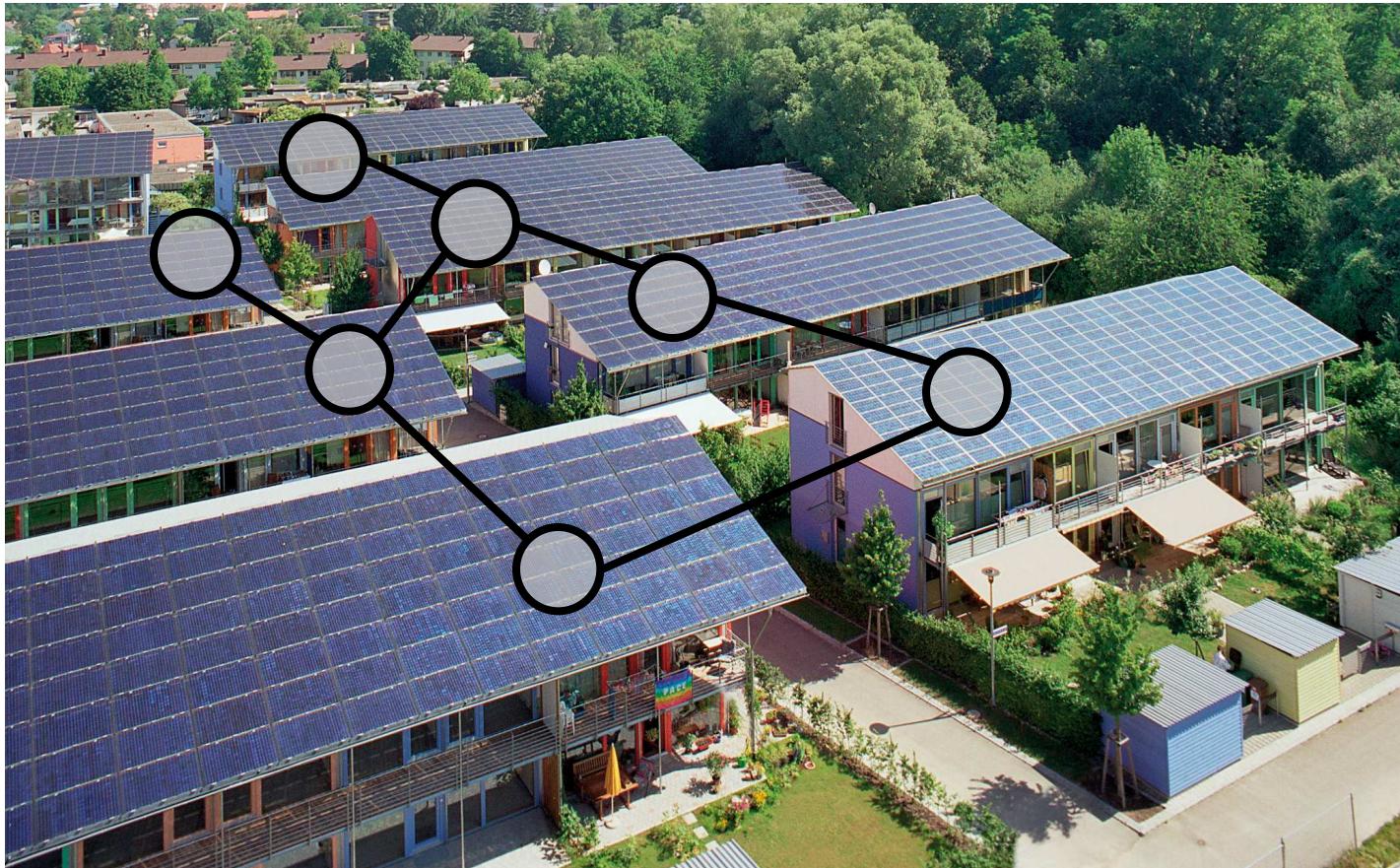
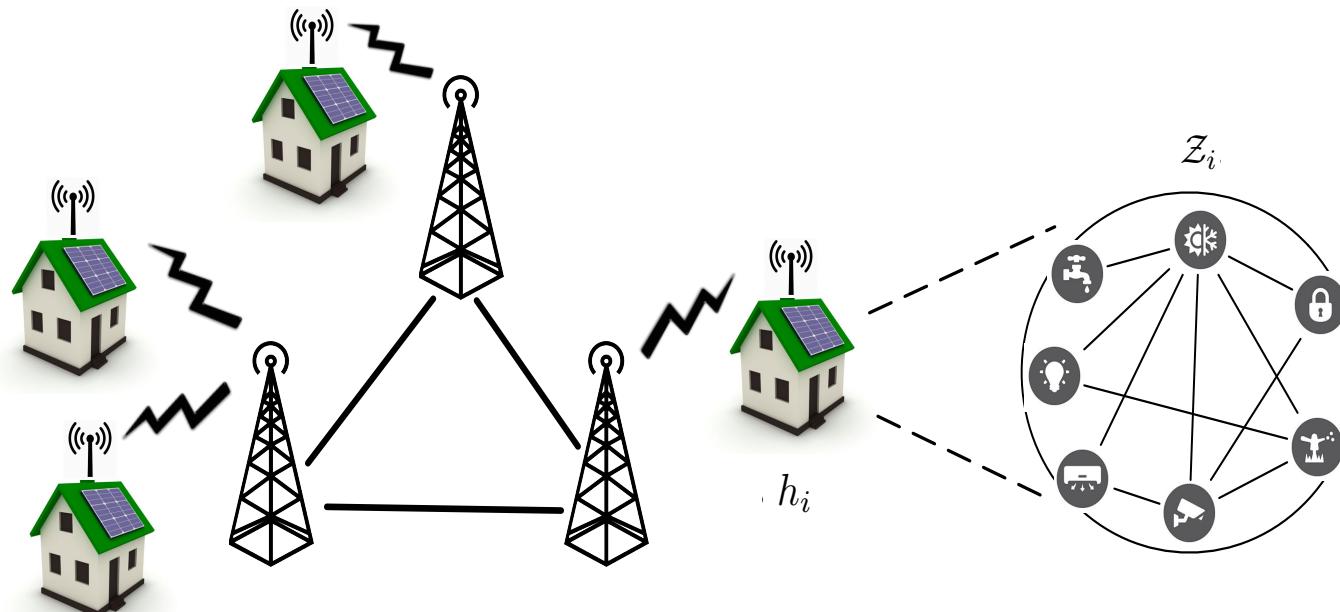


Fig.3

Smart Home Device Scheduling (SHDS)

A SHDS problem is composed of:

- A neighborhood of smart homes.
- A set of smart electric devices within each home.
- A time horizon for the device scheduling.



Smart Home Device Scheduling (SHDS)

A SHDS problem is composed of:

- A neighborhood of smart homes.
- A set of smart electric devices within each home.
- A time horizon for the device scheduling.
- A pricing function expressing cost per kWh of energy consumed.

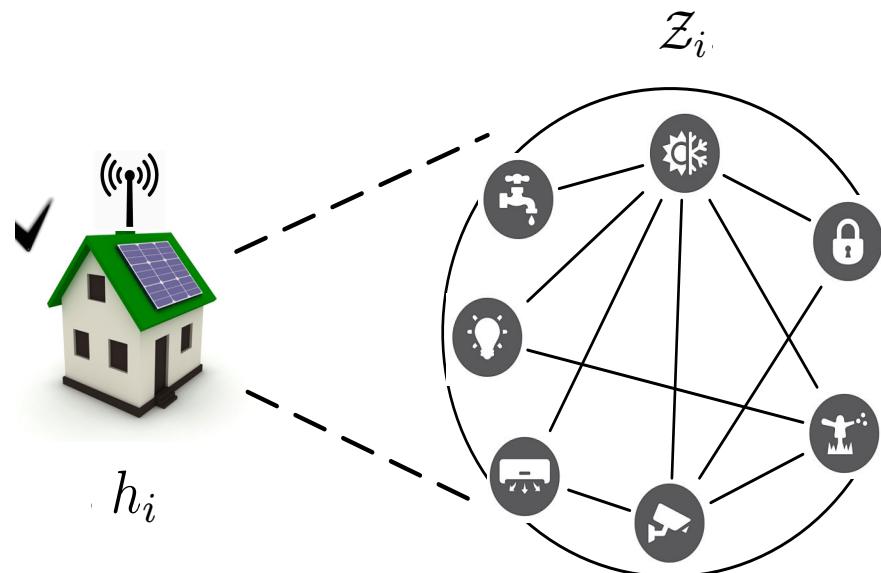
time start	0:00	8:00	12:00	14:00	18:00	22:00
time end	7:59	11:59	13:59	17:59	21:59	23:59
price (\$)	0.198	0.225	0.249	0.849	0.225	0.198

Pacific Gas & Electric Co. pricing schema

Smart Home

A smart home has:

- A set of smart devices it can control (e.g, HVAC, roomba)



Smart Home

A smart home has:

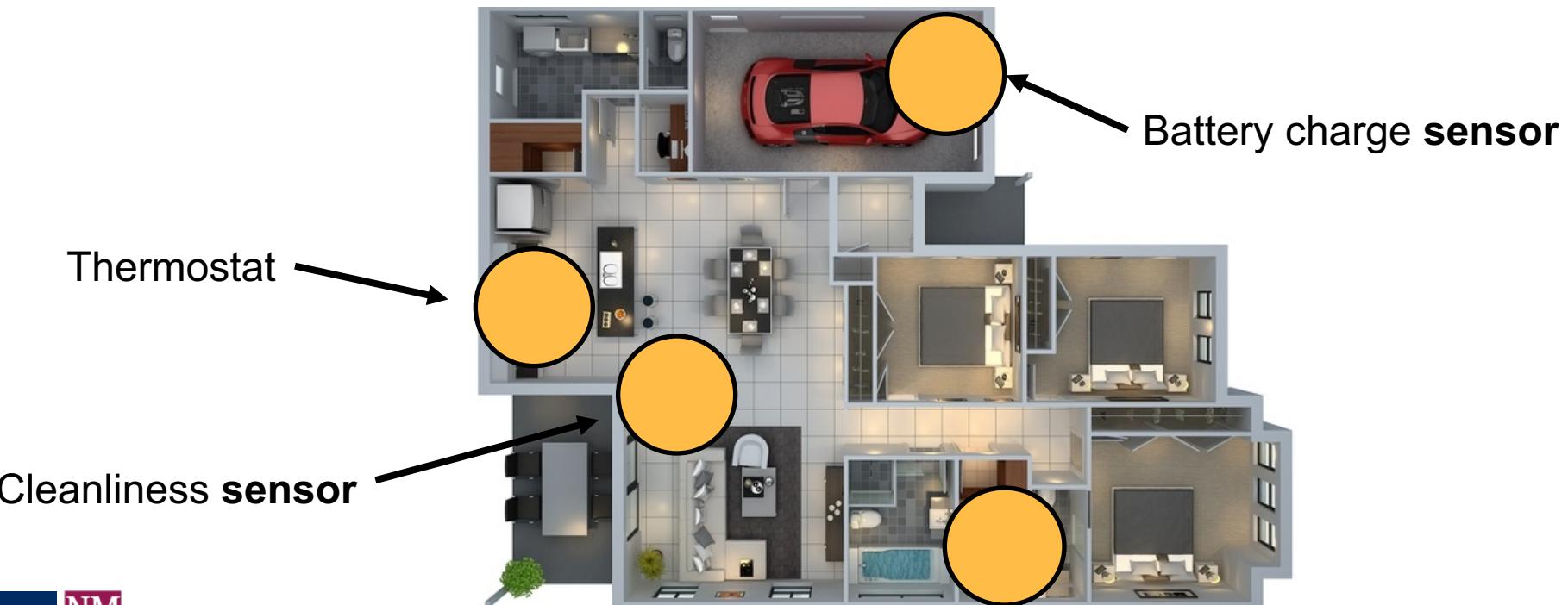
- A set of smart devices it can control (e.g., HVAC, roomba)
- A set of locations (e.g., living room, kitchen)



Smart Home

A smart home has:

- A set of smart devices it can control (e.g, HVAC, roomba)
- A set of locations (e.g., living room, kitchen)
- A set of sensors (e.g., cleanliness, temperature)



Smart Devices (Actuators)

A smart device is defined with a

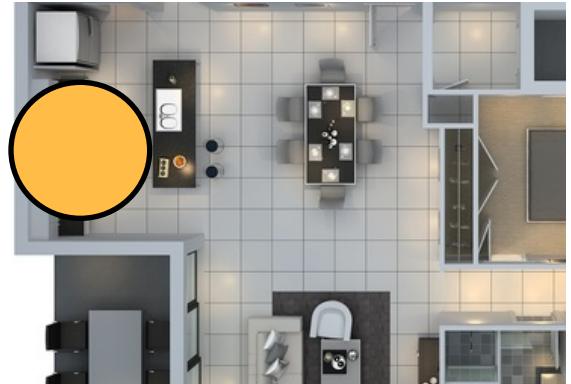
- **Location**: where the device can act (e.g., living room)
- **Actions** it can perform (clean, charge, stop) and the power consumption associated to them
- Sensors' **states properties** it affects (e.g., cleanliness, battery charge)



Action	State property	Power (kW/h)
run	cleanliness, battery charge	0.0
charge	battery charge	0.26
stop		0.0

Smart Devices (Sensors)

- We associate a *predictive model* to each home sensor.
- It describes the transition of a state property from a state s and time t to time $t+1$, when affected by a set of actuators.



A yellow circle highlights the central control panel on the wall, which includes a digital display and several buttons. An arrow points from the word "Thermostat" to this highlighted area.

Effect of the environment

Heater	Oven	Current State	Next State
off	off	12 C	11 C
off	bake	12 C	13.8 C
on	off	12 C	17.5 C
on	bake	12 C	19.3 C

Smart Device Schedules

Scheduling Rules

- **Active rules:** specify user-defined objectives on a desired state of the home. E.g.,

living-room cleanliness ≥ 75 before 1800

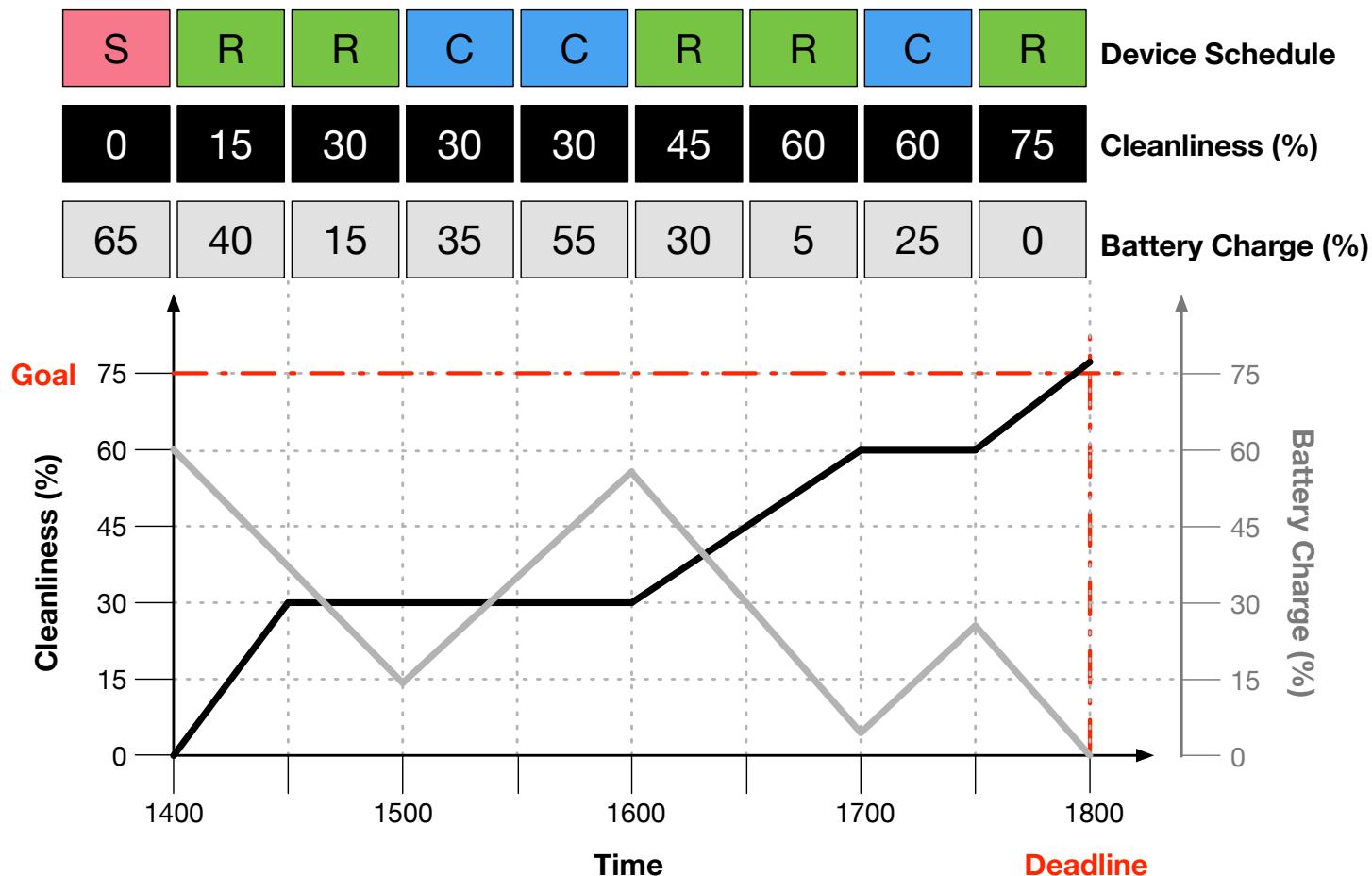
- **Passive rules:** define implicit constraints on devices. E.g.,

$z_v \text{ battery-charge} \geq 0 \text{ always}$

$z_v \text{ battery-charge} \leq 100 \text{ always}$

Smart Device Schedules

Schedule: A sequence of actions for the home devices.



Smart Home Device Scheduling (SBDS)

- SHDS objective:

Aggregated monetary cost of the homes schedules

$$\min_{\xi_{Z_i}^{[0 \rightarrow H]}} \alpha_c \cdot C^{\text{sum}} + \alpha_e \cdot E^{\text{diff}}$$

Energy consumption peaks across all homes

Homes' devices schedules

subject to:

$$\forall h_i \in \mathbf{H}, R_p^{[t_a \rightarrow t_b]} \in \mathbf{R}_i : \quad \xi_{\Phi_p}^{[t_a \rightarrow t_b]} \models R_p^{[t_a \rightarrow t_b]}$$

All device scheduling rules must be satisfied

DCOP mapping

SBDS

- A home $h_i \in \mathcal{H}$.
- A device z_j (in building h_i)
- Action j for device z_j .
- Schedule costs for a device z_j
- Device scheduling feasibility
- Energy peak consumption

DCOP

- Agent $a_i \in \mathcal{A}$
- Variable $x_i \in \mathcal{X}$ (controlled by a_i)
- j-th value in domain D_i of variable x_i
- Local soft constraint
- Local hard constraint
- Global soft constraint

Physical Models

- House structural parameters
- Smart Devices
 - Sensors
 - Actuators
- Battery models
- Air Temperature Model
- Water temperature model
- Cleanliness model
- ...



Physical Model (homes)



FIG. 2: Floor plans for a small (left), medium (center), and large (right) house.

Structural Parameters	small	medium	large	Structural Parameters	small	medium	large
house size (m)	6×8	8×12	12×15	U_{roof} (W/(m ² °C))	1.1	1.1	1.1
walls area (m ²)	67.2	96	129.6	lights energy density (W/m ³)	9.69	9.69	9.69
window area (m ²)	7.2	10	16	background load (kW)	0.166	0.166	0.166
U_{walls} (W/(m ² °C))	3.9	3.9	3.9	background heat gain (W)	50	50	50
U_{windows} (W/(m ² °C))	2.8	2.8	2.8	people heat gain (Btu/h)	400	400	400

Battery Models

	Tesla Model S			iRobot Roomba 880
	Slow Charge	Regular Charge	Super Charger	
V_b	240	240	240	120
E_b	354 Ah	354 Ah	354 Ah	3 Ah
C^+	48 A	72 A	500 A	1.25 A
C^-	60 A	60 A	60 A	0.75 A
b_α^+	7 hr 22 min	5 hr	43 min	2 hr 24 min
b_α^-	6 hr	6 hr	6 hr	4 hr



Dataset

- 624 instances of increasing difficulty.
- Homes of 3 sizes (small, medium, large)

City	Density (km ²)
Dos Moines, IA	718
Boston, MA	1357
San Francisco	3766

Parameters	
Homes	[7, 7523]
Coalitions	[1, 1024]
Devices per home	[4, 20]
Rules	> above
Horizon	12

- We provide our instance generator! Allows different horizons.

Dataset

$\langle \text{location} \rangle$	$\langle \text{state property} \rangle$	$\langle \text{relation} \rangle$	$\langle \text{goal state} \rangle$	$\langle \text{time} \rangle$
Room	air temperature	$r \in \{>, \geq\}$	$g_1 \in [17, 24]$	$\langle \text{time} \rangle$
Room	floor cleanliness	$r \in \{>, \geq\}$	$g_2 \in [50, 99]$	$\langle \text{time} \rangle$
Electric Vehicle	charge	$r \in \{>, \geq\}$	$g_3 \in [50, 99]$	$\langle \text{time} \rangle$
Water heater	temperature	$r \in \{>, \geq\}$	$g_4 \in [15, 40]$	$\langle \text{time} \rangle$
Clothes Washer	laundry wash	$r \in \{\geq\}$	$g_5 \in \{45, 60\}$	$\langle \text{time} \rangle$
Clothes Dryer	laundry dry	$r \in \{\geq\}$	$g_6 \in \{45, 60\}$	$\langle \text{time} \rangle$
Oven	bake	$r \in \{=\}$	$g_7 \in \{60, 75, 120, 150\}$	$\langle \text{time} \rangle$
Dishwasher	dish cleanliness	$r \in \{\geq\}$	$g_8 \in \{45, 60\}$	$\langle \text{time} \rangle$

TABLE 6: Scheduling (active) rules

$\langle \text{location} \rangle$	$\langle \text{state property} \rangle$	$\langle \text{relation} \rangle$	$\langle \text{goal state} \rangle$	$\langle \text{location} \rangle$	$\langle \text{state property} \rangle$	$\langle \text{relation} \rangle$	$\langle \text{goal state} \rangle$
Room	air temperature	\geq	0	EV	charge	\leq	100
Room	air temperature	\leq	33	Water heater	temperature	\geq	10
Room	floor cleanliness	\geq	0	Water heater	temperature	\leq	55
Room	floor cleanliness	\leq	100	Clothes Washer	laundry wash	\leq	g_5
Roomba	charge	\geq	0	Clothes Dryer	laundry dry	\leq	g_6
Roomba	charge	\leq	100	Oven	bake	\leq	g_7
EV	charge	\geq	0	Dishwasher	dish cleanliness	\leq	g_8

TABLE 7: Scheduling (passive) rules

Dataset

- Upper bounds for all the instances released.
- Uncoordinated approach.
- Communication and coordination of the MAS is implemented via the JADE framework.
- Each agent uses an internal CP solver (JaCoP) to solve its local scheduling problem.
- More on this on **Thursday - Session 4D**
14:30-16:10 Novel Applications in Smart Grids and Mobility



Smart devices



A Raspberry PI with a dangle

Conclusions

- Distributed Constraint Optimization – great potential, very exciting era.
- Review DCOP assumptions – need for realistic benchmark.
- Smart Home Device Scheduling Problem as a DCOP.
- New dataset for SHDS problems – available to the community

https://github.com/nandofioretto/SHDS_dataset

References:

Fig. 1: <http://goo.gl/5znqip>
Fig. 2: goo.gl/dqwUz2
Fig. 3: goo.gl/WFzMhv

Conclusions

- Distributed Constraint Optimization – great potential, very exciting era.
- Review assumptions – need for realistic benchmark.
- Smart Home Device Scheduling Problem as a DCOP.
- New dataset for SHDS problems – available to the community

https://github.com/nandofioretto/SHDS_dataset

Thank You!

References:

Fig. 1: <http://goo.gl/5znqip>
Fig. 2: goo.gl/dqwUz2
Fig. 3: goo.gl/WFzMhv