A Multiagent System Approach to Schedule Devices in Smart Homes

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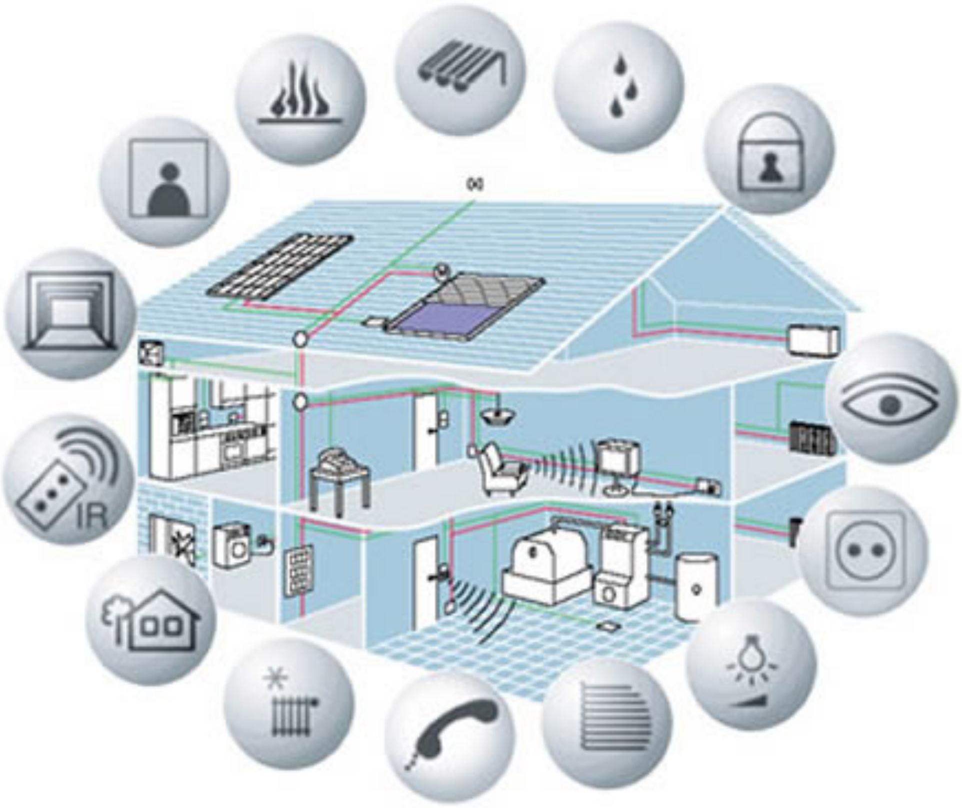
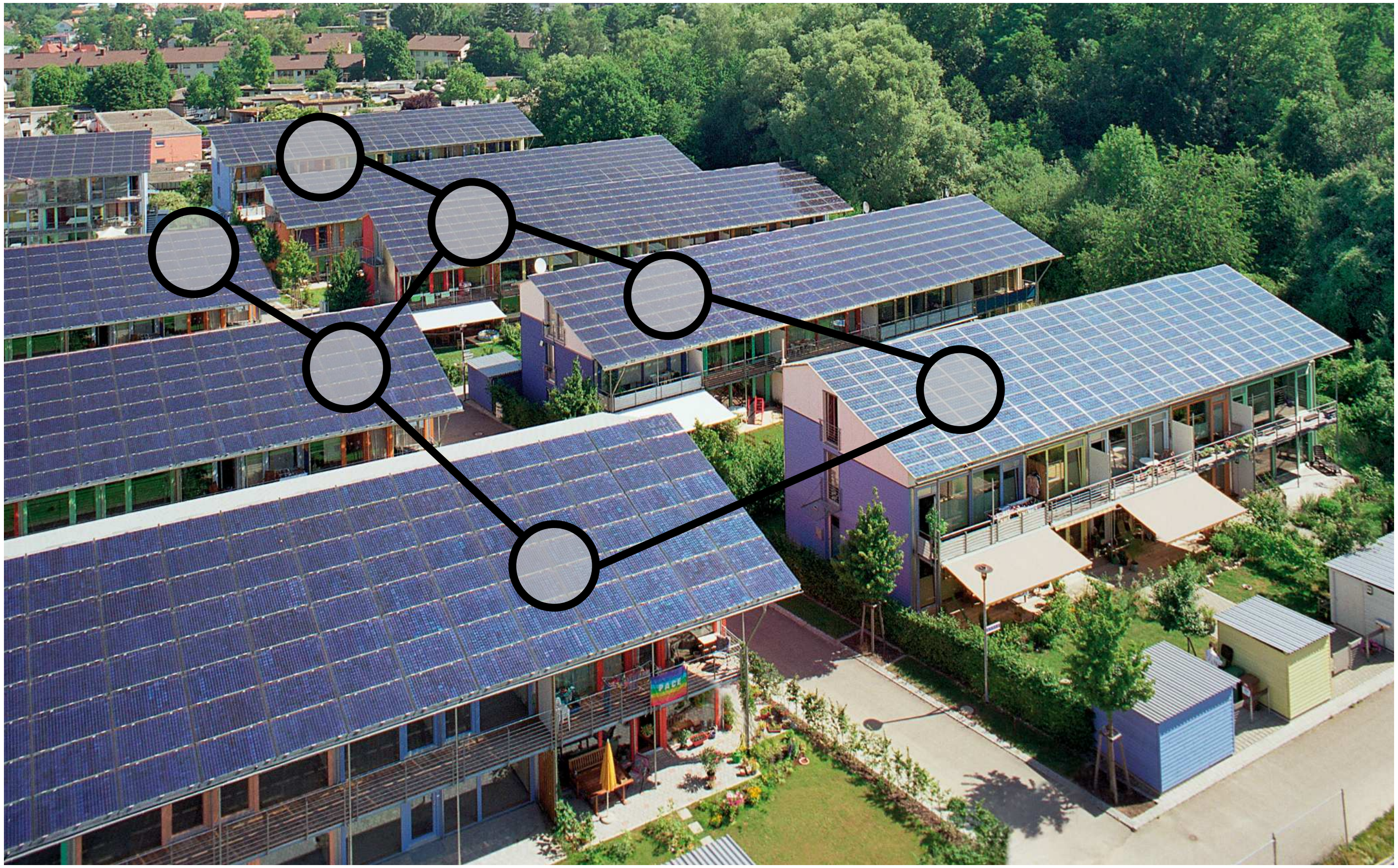
Home Automation



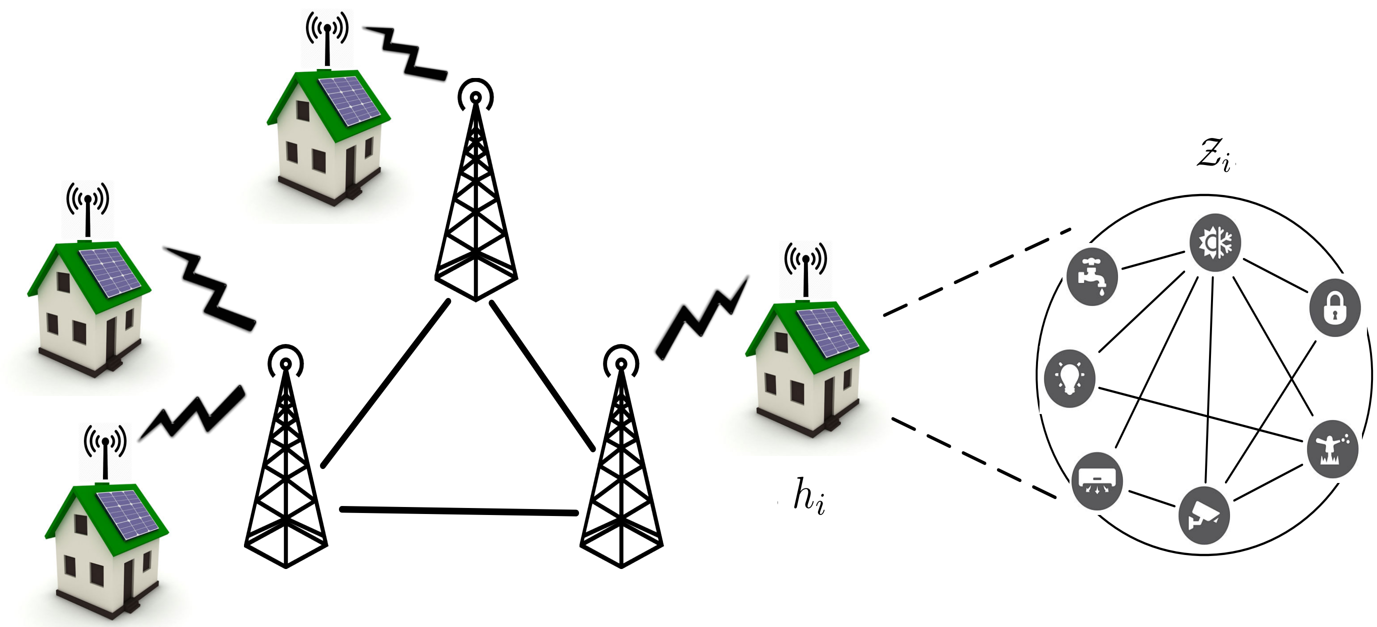
Network of smart homes



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.



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- 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.

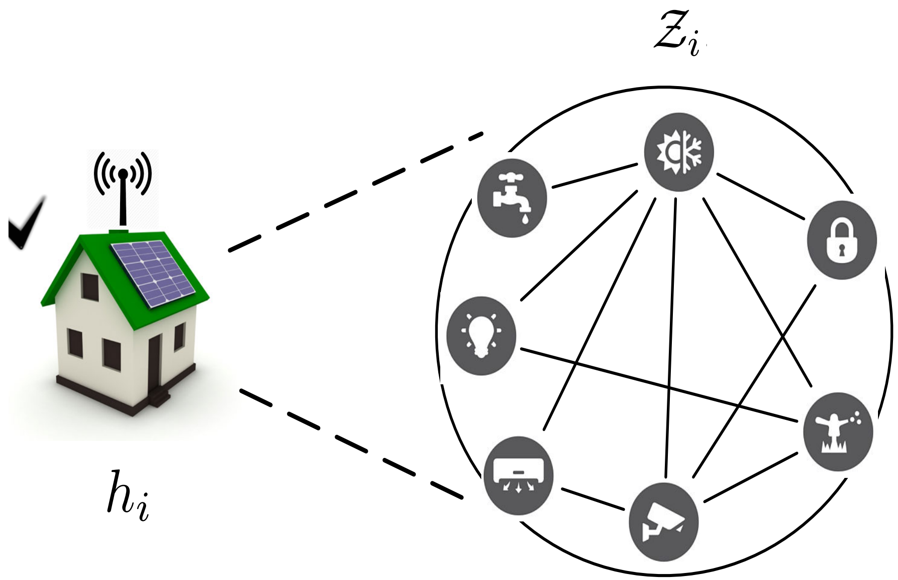
time start	0:00	8:00	12:00	14:00	18:00	22:00
time end	7:59	11:59	13:59	17:59	21:59	23:59
price ($)	0.198	0.225	0.249	0.849	0.225	0.198

Pacific Gas & Electric Co. pricing schema

Smart Home

A smart home has:

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



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- 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

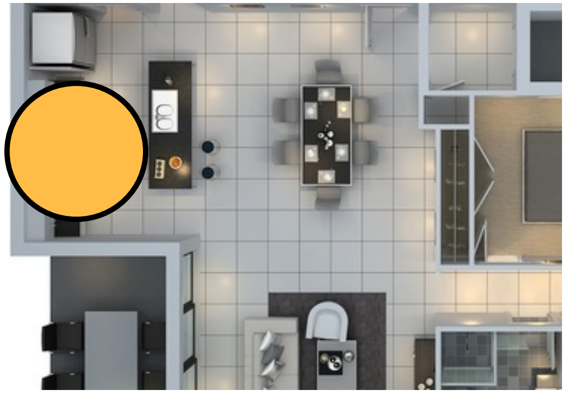
- Location: where the device can act (e.g., living room)
- Actions it can perform (clean, charge, stop) and the power consumption associated to them
- Sensors' states properties it affects (e.g., cleanliness, battery_charge)

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.

Thermostat



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

Effect of the environment

Smart Device Schedules

Scheduling Rules

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

$$\texttt{living\_room cleanliness} \geq \texttt{75 before 1800}$$

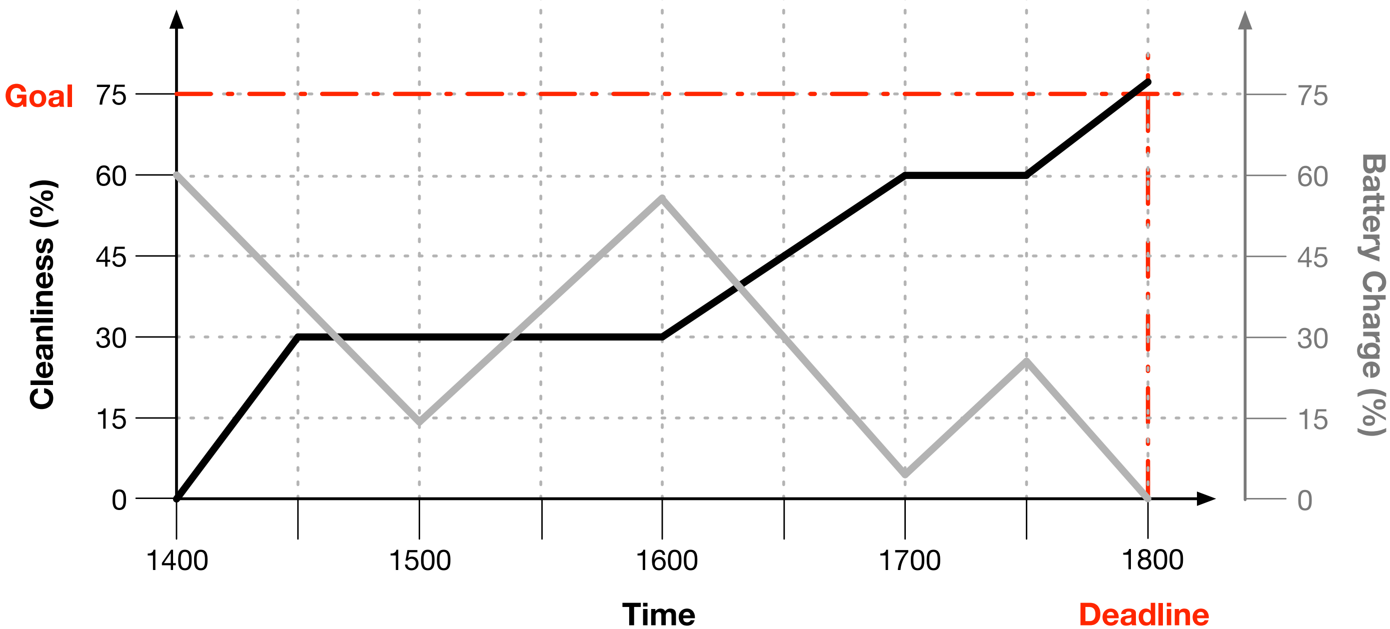
- **Passive rules**: define implicit constraints on devices. E.g.,

$$z_v \ \texttt{battery\_charge} \geq \texttt{0 always}$$
$$z_v \ \texttt{battery\_charge} \leq \texttt{100 always}$$

Smart Device Schedules

Schedule: A sequence of actions for the home devices.

S	R	R	C	C	R	R	C	R	**Device Schedule**
0	15	30	30	30	45	60	60	75	**Cleanliness (%)**
65	40	15	35	55	30	5	25	0	**Battery Charge (%)**



Smart Home Device Scheduling (SBDS)

- SHDS objective:

$$\min_{\xi_{\mathbf{z}_i}^{[0\rightarrow H]}} \quad \alpha_c \cdot \overbrace{C^{\text{sum}}}^{\text{Aggregated monetary cost of the homes schedules}} + \alpha_e \cdot \underbrace{E^{\text{diff}}}_{\text{Energy consumption peaks across all homes}}$$

Homes' devices schedules

subject to:

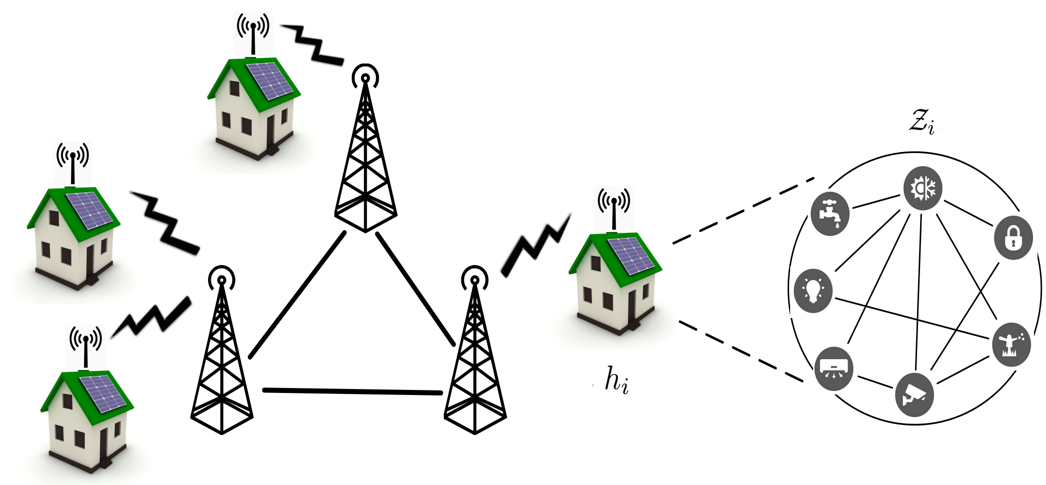
$$\forall h_i \in \mathbf{H}, R_p^{[t_a \rightarrow t_b]} \in \mathbf{R}_i : \quad \xi_{\Phi_p}^{[t_a \rightarrow t_b]} \models R_p^{[t_a \rightarrow t_b]}$$

All scheduling rules must be satisfied

Distributed Constraint Optimization

$<\mathcal{X}, \mathcal{D}, \mathcal{F}, \mathcal{A}, \alpha>$:

- $\mathcal{X}$: 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.



Distributed Constraint Optimization

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- GOAL: Find a cost minimal assignment.

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

Distributed Constraint Optimization

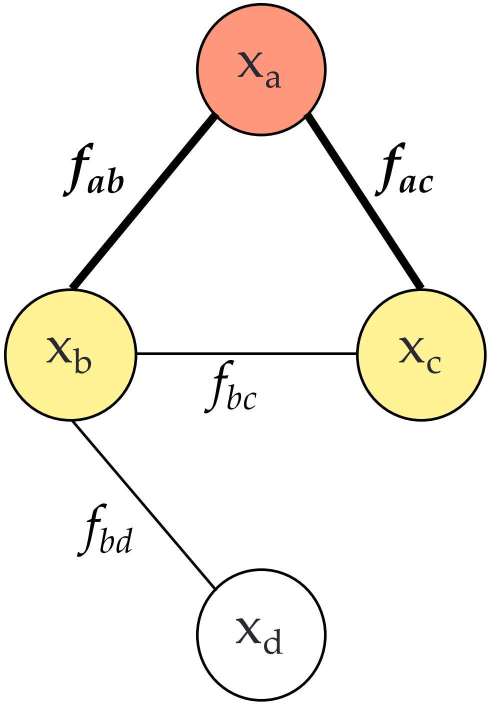
- Agents coordinate an assignment for their variables.
- Agents operate distributedly.

Communication:

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

Knowledge:

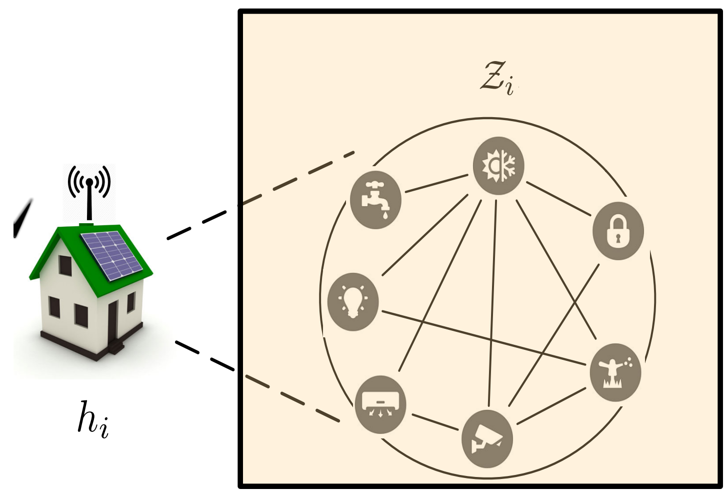
- Restricted to agent's sub-problem.



Solution Approach

SH-MGM: Adaptation of a local search DCOP algorithm (MGM).

1. Agents independently search for a feasible schedule for their local devices.

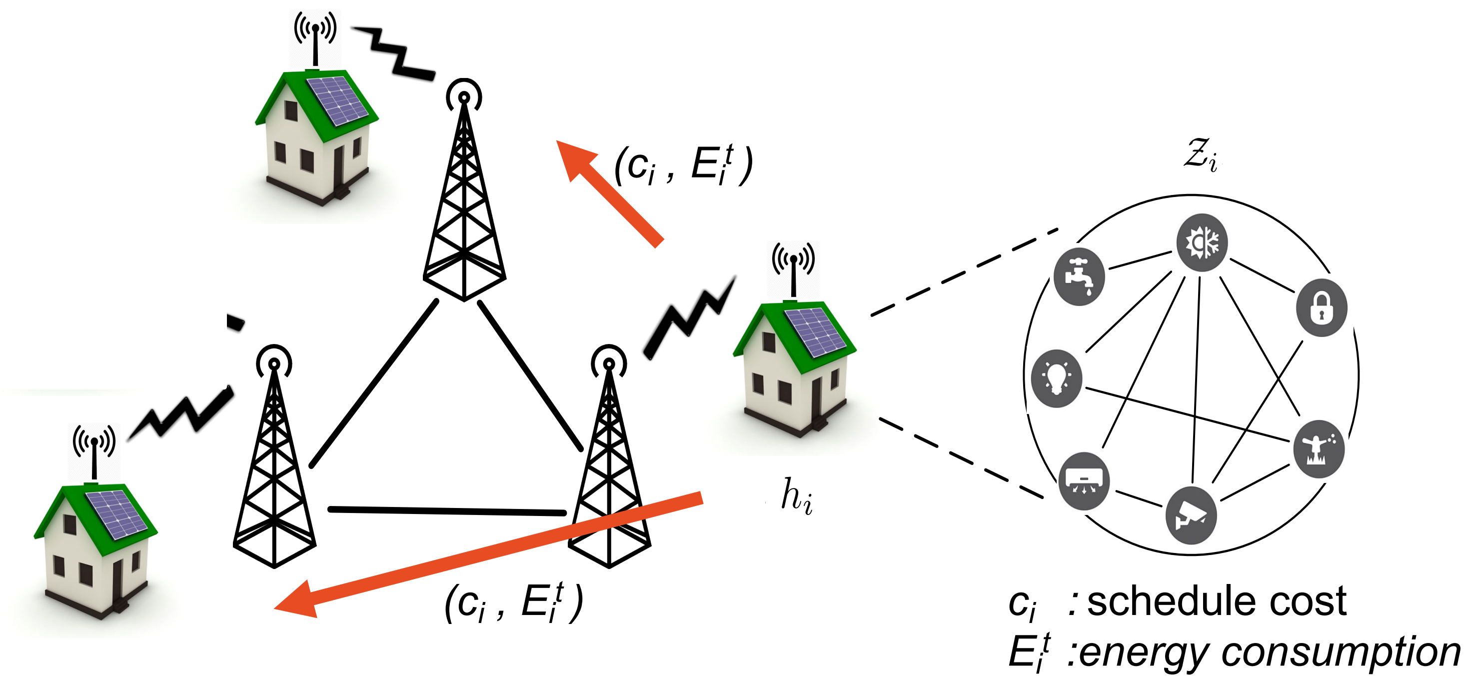


c_i : schedule cost
E_i^t :energy consumption

Solution Approach

SH-MGM: Adaptation of a local search DCOP algorithm (MGM).

1. Agents independently search for a feasible schedule for their local devices.
2. Schedule costs and energy consumption are broadcasted to all other agents.

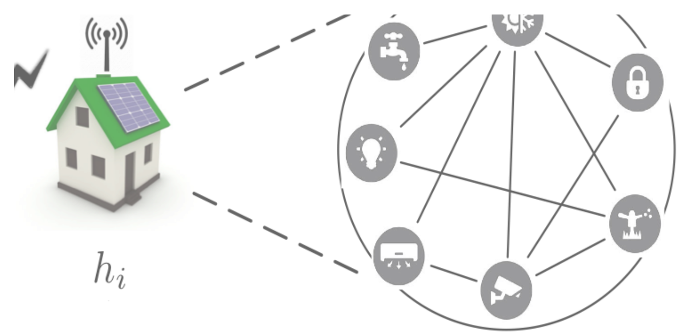


Solution Approach

SH-MGM: Adaptation of a local search DCOP algorithm (MGM).

3. Upon receiving all other agents costs and energy consumptions:
    - Computes the objective cost with its current schedule.
    - Within a time limit, it finds a new solution to its local subproblem that is no worse than the current solution.

$$\alpha_c \cdot c_i(\underbrace{\hat{\xi}_{\mathbf{Z}_i}^{[0\to H]}}_{\text{current schedule}}) + \alpha_e \cdot \hat{E}^{\text{diff}} \le \alpha_c \cdot c_i(\overbrace{\xi_{\mathbf{Z}_i}^{[0\to H]}}^{\text{new schedule}}) + \alpha_e \cdot E^{\text{diff}}$$



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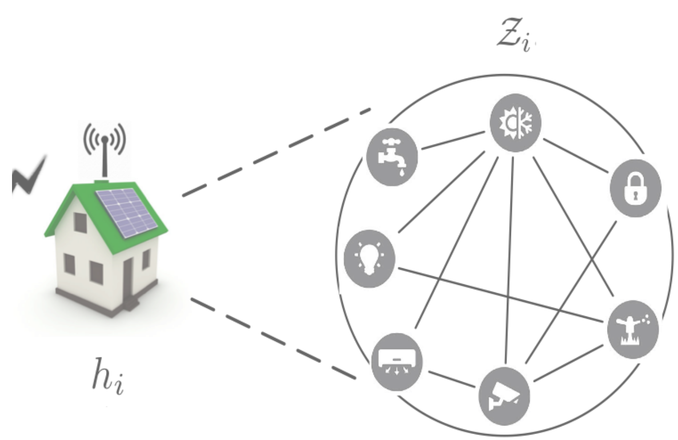
3. Upon receiving all other agents costs and energy consumptions:
   - Computes the objective cost with its current schedule.
   - Within a time limit, it finds a new solution to its local subproblem that is no worse than the current solution.
   - It computes the gain G_i between its current and new solutions, and broadcast it to all other agents.

$$G_i = \left(\alpha_c \cdot c_i(\xi_{\mathbf{Z}_i}^{[0 \to H]}) + \alpha_e \cdot E^{\text{diff}}\right) - \left(\alpha_c \cdot c_i(\hat{\xi}_{\mathbf{Z}_i}^{[0 \to H]}) + \alpha_e \cdot \hat{E}^{\text{diff}}\right)$$



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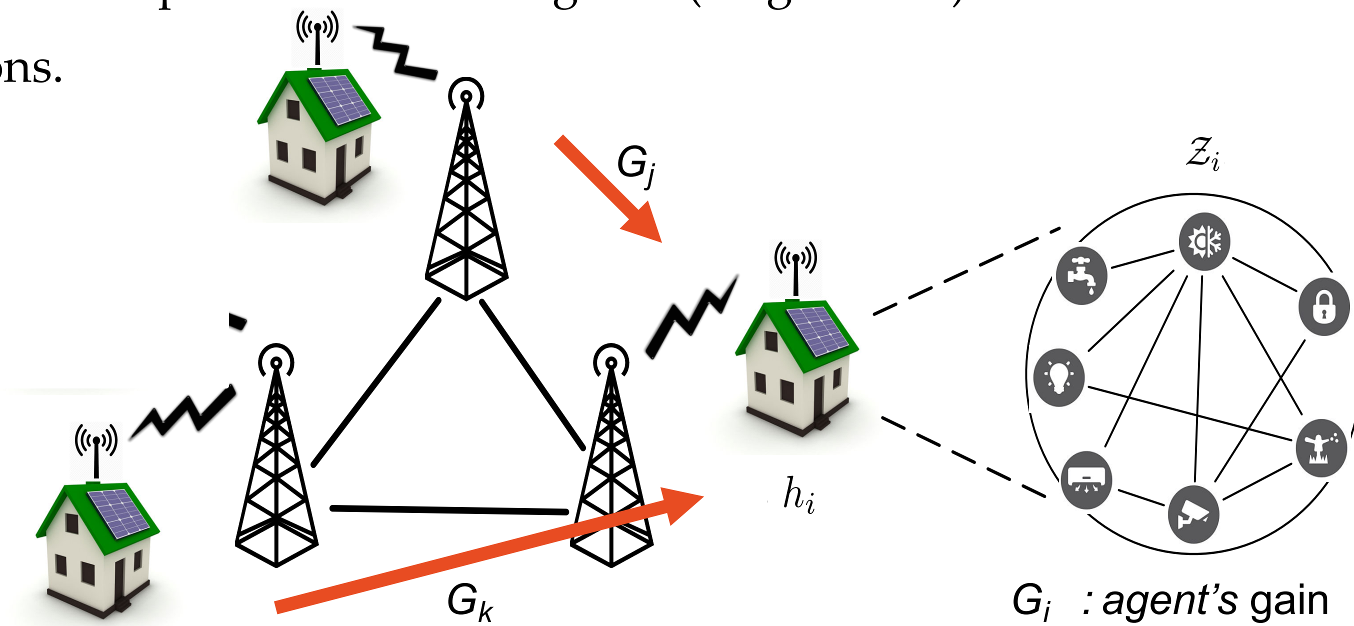
4. Upon receiving all other agents' gains G_k, it checks if the agent has the largest gain among all those received. If so, it updates its schedule to the new schedule, otherwise it retains its old schedule.

5. The process repeats untill convergence (all gains = 0) or a fixed number of iterations.



Evaluation: Settings

- 7 Raspberry Pis connected via a LAN.
- Each controlling 9 smart actuators.
- 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.

Smart devices

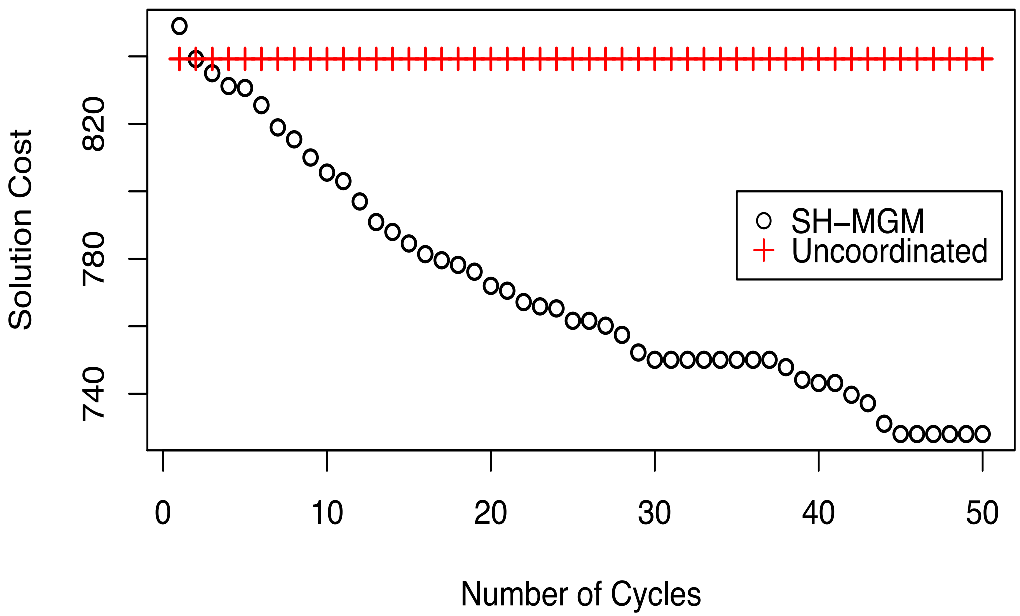
A Raspberry PI with a dangle

Evaluation: Physical MAS Experiments

Settings:

- H = 12 (step = 30 min)
- Realistic device consumptions and environment settings (see our paper at OPTMAS)
- CP timeout = 10 sec

SH-MGM vs. Uncoordinated approach



Main Results:

- SH-MGM finds better solutions than a simple uncoordinated approach.

- Solution quality increases with the number of cycles.

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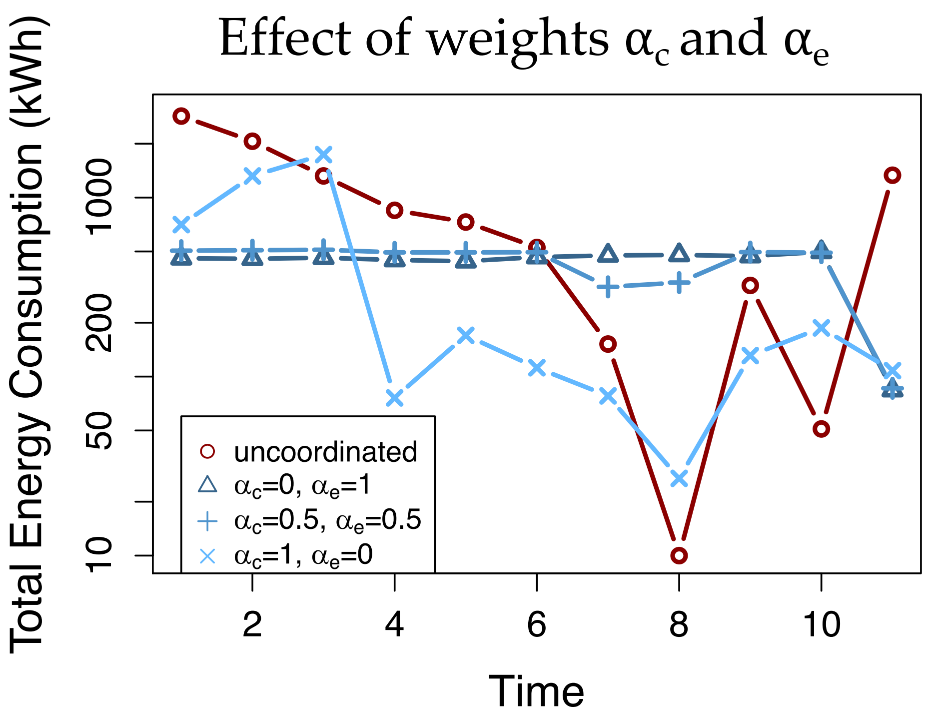

Main Results:
- SH-MGM has better effects on peaks reduction w.r.t an uncoordinated approach.

Evaluation: Large scale simulation

Settings:

- H = 12 (step = 30 min)
- Realistic device consumptions and environment settings
- CP timeout = 10 sec

City	k	convergence time (sec)	avg. l.s. time (sec)	network load	avg. cost ($/day)	max peak (kWh)
Des Moines	-	7.8	0.72	0	3.84	2852
	1	1044	9.62	9.8e+5	2.18	508
	5	304	9.44	4.8e+4	1.89	579
	10	218	9.37	1.2e+4	1.71	607
Boston	-	13.9	1.59	0	3.79	6034
	1	2821	9.91	1.2e+7	2.22	985
	5	866	9.91	6.7e+5	2.05	1058
	10	527	9.89	1.8e+5	1.88	1111
San Francisco	-	26.6	4.51	0	3.81	11944
	1	4238	10.4	1.7e+8	2.36	1870
	5	940	10.4	1.6e+6	2.06	2120
	10	679	10.7	1.1e+6	2.01	2310

Conclusions and Future Work

- Exciting era for multi-agent systems in smart homes!
- Smart Home Device Scheduling Problem and cast it as a DCOP.
- SH-MGM: a local search-based algorithm to solve SHDS problems.
- Results:
  - SH-MGM finds better solutions than a simple uncoordinated method.
  - Feasibility established for using a local search-based approach implemented on hardware with limited storage and processing power.
- **Dataset available for download:**

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Thank You!