Joint JST-NSF-DFG-RCN Workshop on
Distributed Energy Management Systems

Prediction and Optimization of EMS Using In-Vehicle Batteries and Their Aggregation

20th Apr., 2015

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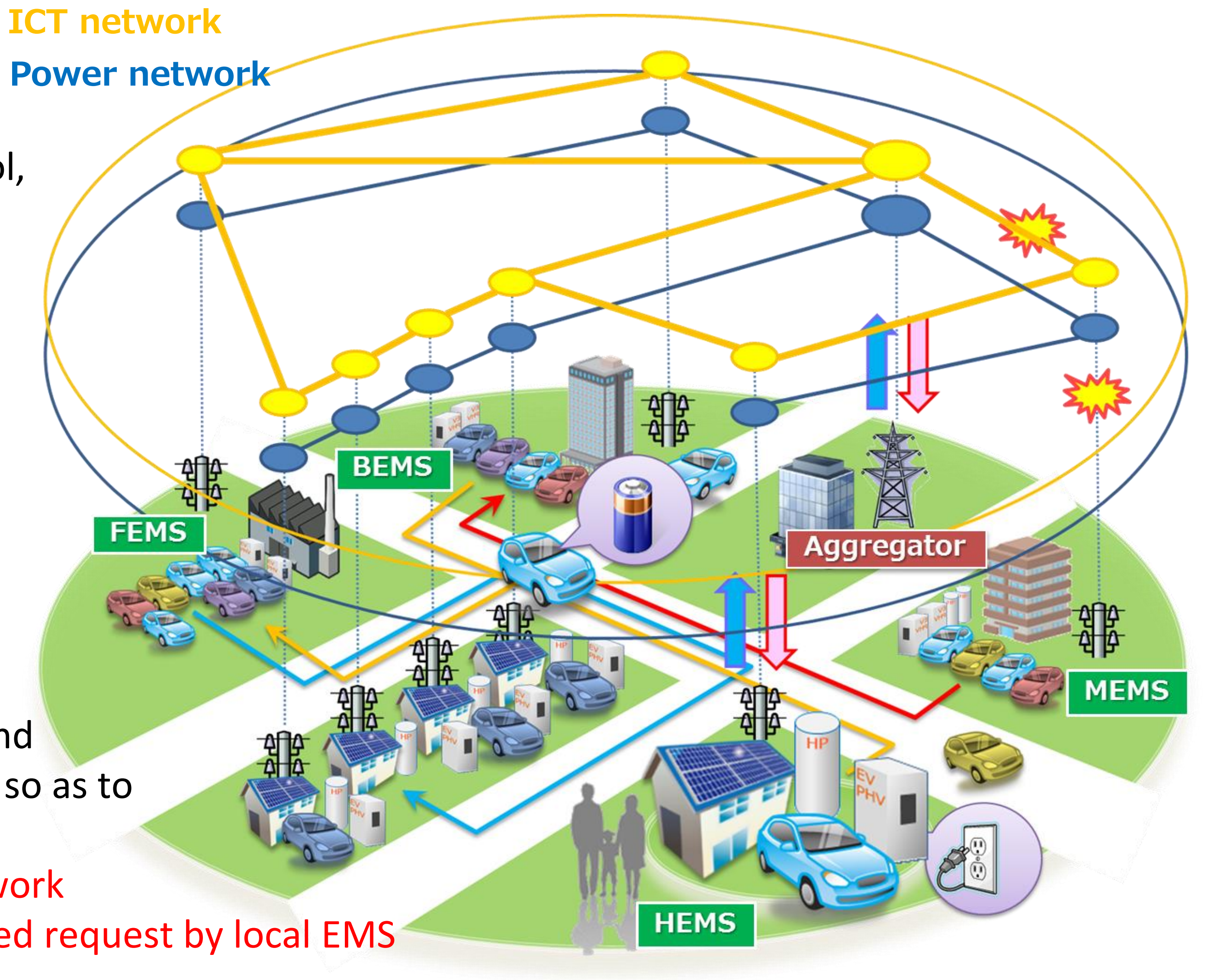
Nagoya University

Overview of EMS using In-vehicle batteries



Agent type

Home, Condominium Building, Factory, School, Hospital, Vehicle, and EMS aggregator

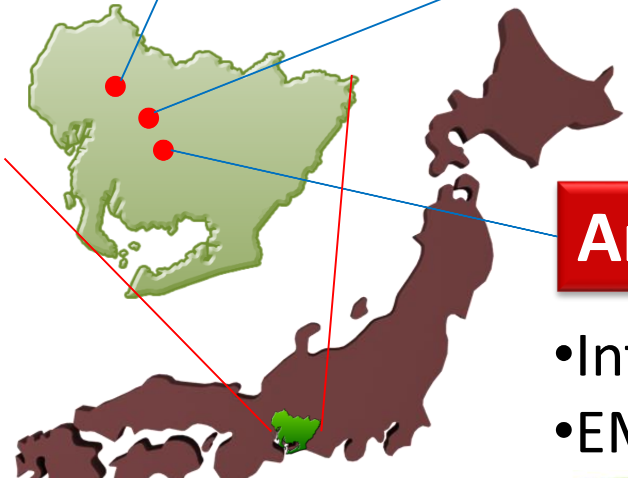
Local agents

Have local EMS, which tries to minimize the energy cost locally.
Personalized EMS

Smart aggregator

Specify a constraints and incentive on local EMS so as to balance supply and demand in power network considering personalized request by local EMS

Collaboration with demonstrative projects using in-vehicle battery



Nagoya University

Toyota city (HEMS+PHV+HP)

- How to use PHV for HEMS (67 households)
- Cooperation of PHV and HPHW

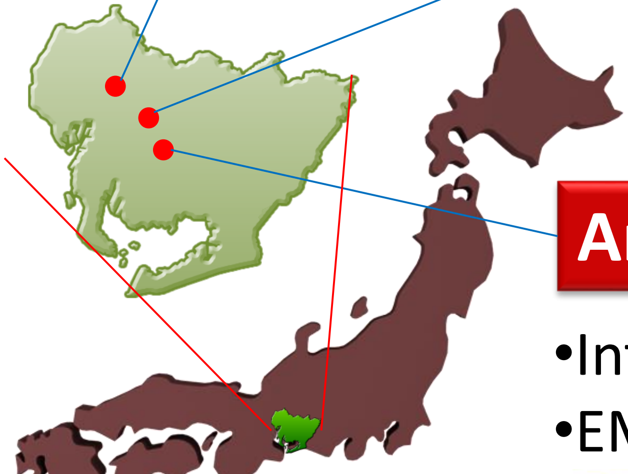
Anjo city (EV Sharing)

- Integration of ITS and EMS
- EMS at EV station

Delaware Univ.（GIV+V2G）

- Vehicle to Grid
- Ancillary service

Collaboration with demonstrative projects using in-vehicle battery



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Collected data set in Toyota city

A. Toyota city real-world demonstration project (2010-2014)
- Target: 67 households, school, convenience store etc.
- Equipment:
  - All houses: electric power source, PV (3-5kW), home battery (5kWh) and a PHV.
  - About 30 houses: fuel cell, charging station for Vehicle to Home (V2H).

	Category	Contents
1	Purchasing Electricity	Current purchasing electricity [W]
2	Selling Electricity	Current selling electricity [W]
3	Total electricity consumption	Current total electricity consumption [W]
4	Electricity at each section in the house	Current electricity consumption at each section in the house [W]
5	Home battery	Current State-of-Charge (SOC) [%]
		Current charge/discharge electricity [W]
		Charging/discharging capacity [Wh]
6	PV generation	Current generated output [W]

	Category	Contents
7	PHV	Plug information [connected/disconnected]
		Information of charging [charging/finished]
		Current State-of-Charge (SOC) [%]
8	Eco Cute Heat pump	Amount of hot water in tank [L]
		Current electricity consumption [W]
9	Water supply	Total used amount [L]

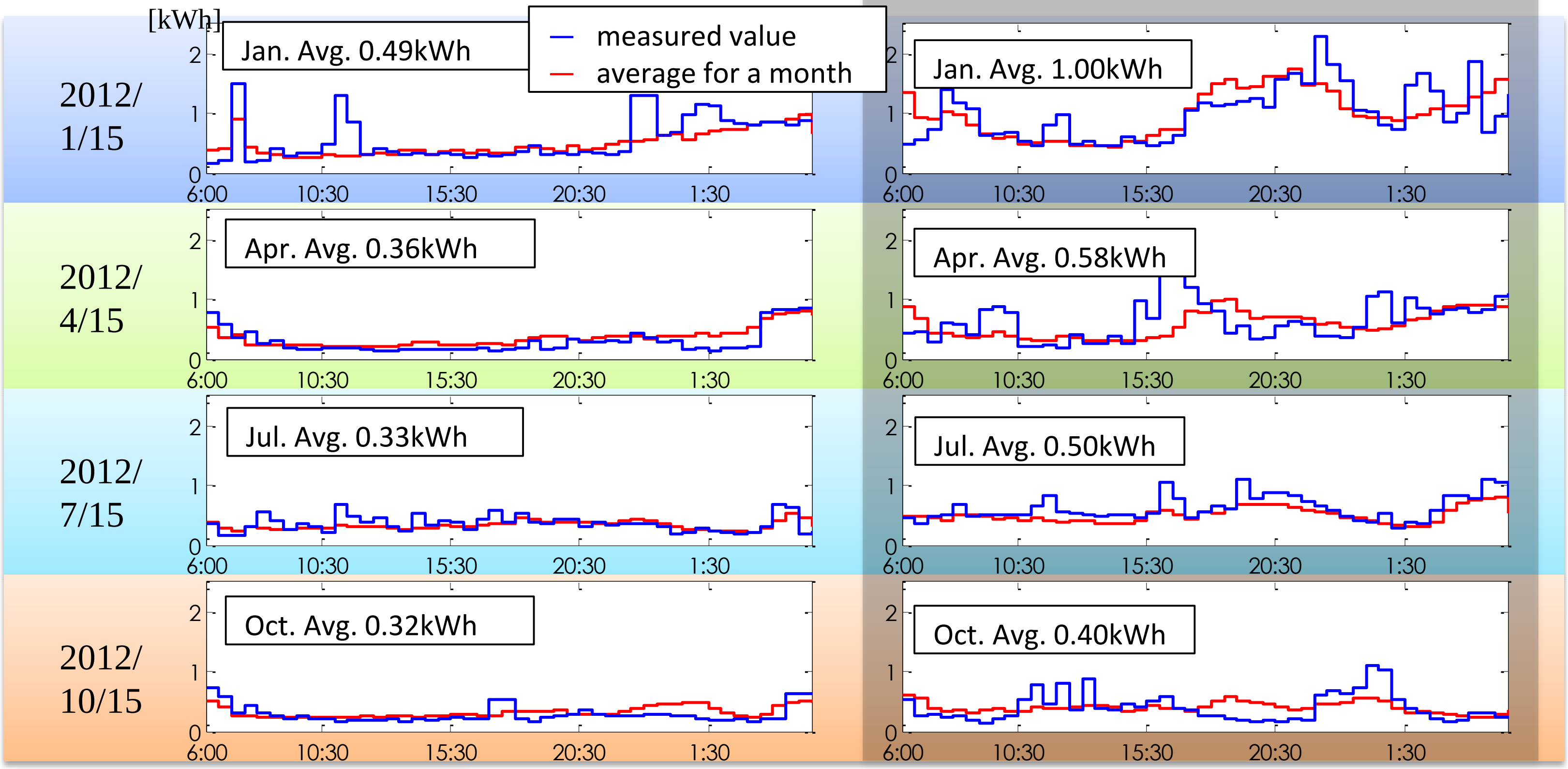
Data is logged every 1minute

Energy consumption and vehicle use are observed simultaneously

Samples of Power Consumption (Two Households and School)

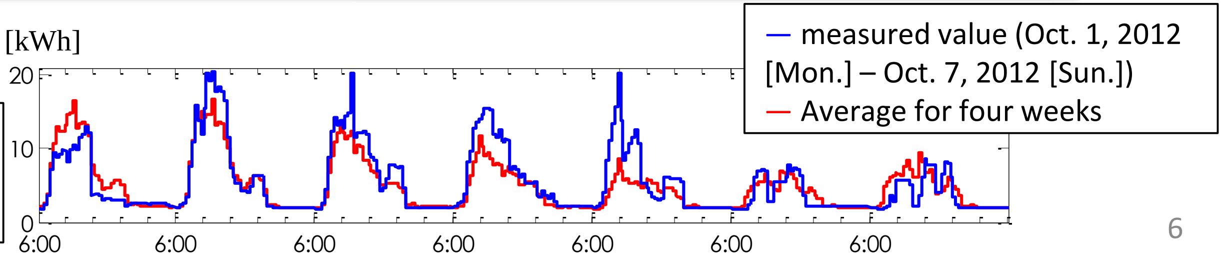
ID = edms10F 2 people, day shift, Eco Cute

ID = edms20A 6 people (2 children), day shift, Eco Cute

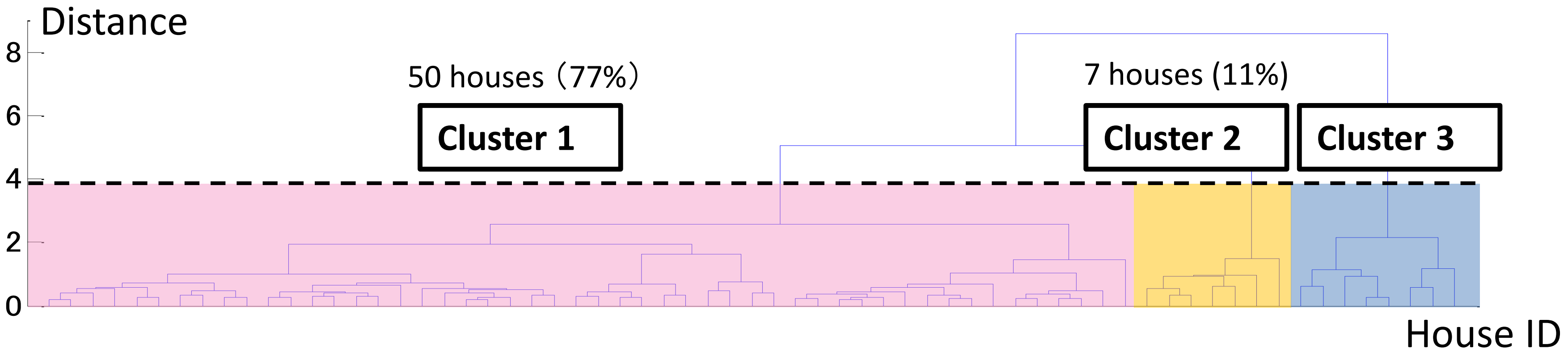


* Without charge of batteries

Electricity Consumption at a elementary school (no electricity generating installation)



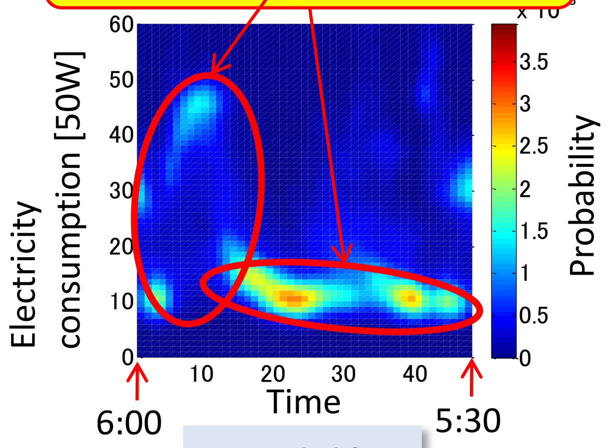
Clustering of Power consumption (March to May, 2013)



Statistics of power consumption in one day for each cluster.

Cluster 1

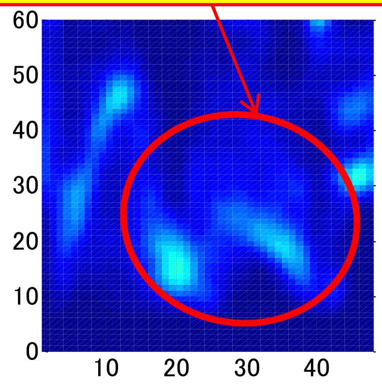
AM: High average, high variance
PM: Low average with small var.



EDMS 20E

Cluster 2

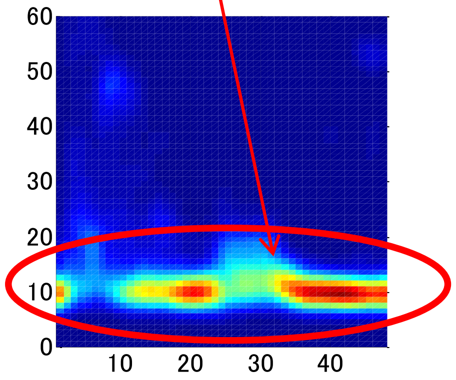
High average, high variance
(High human activity)



EDMS 20A

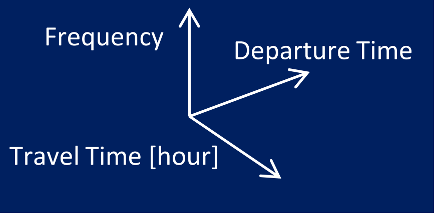
Cluster 3

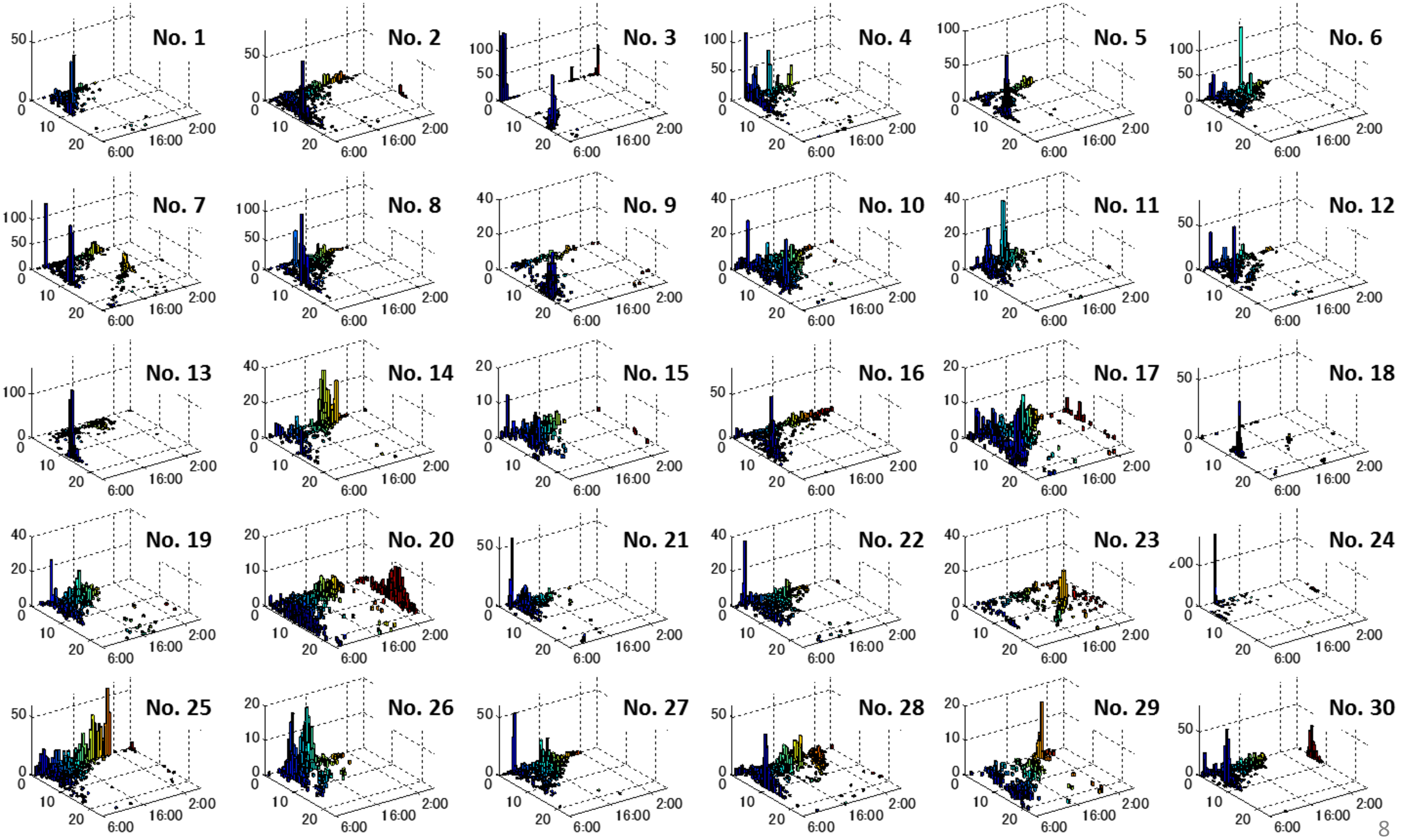
Low average with small var.



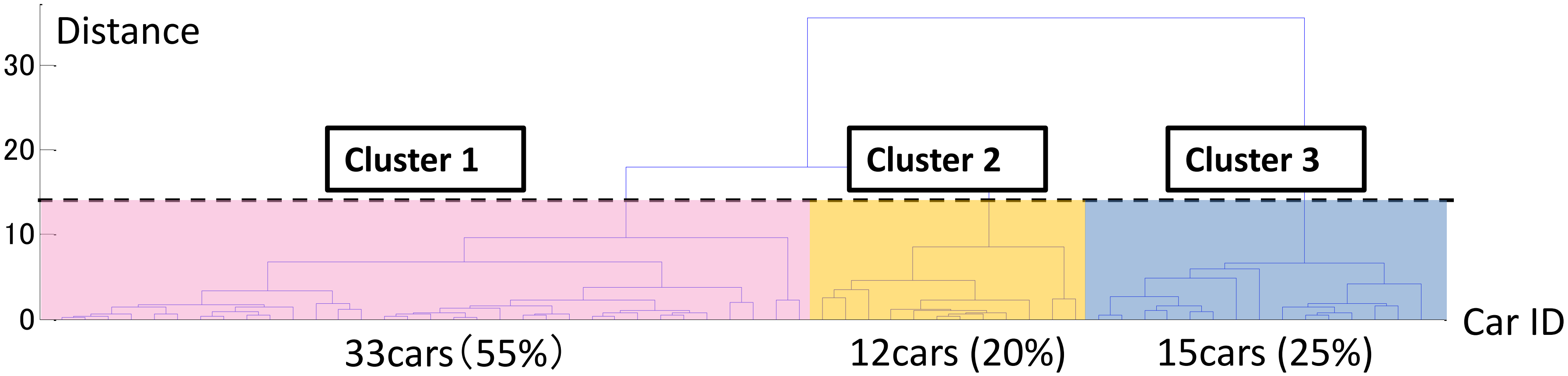
HEMS 40E

Sample Data of Vehicle Use (Nov. 2012 – Jan. 2015)

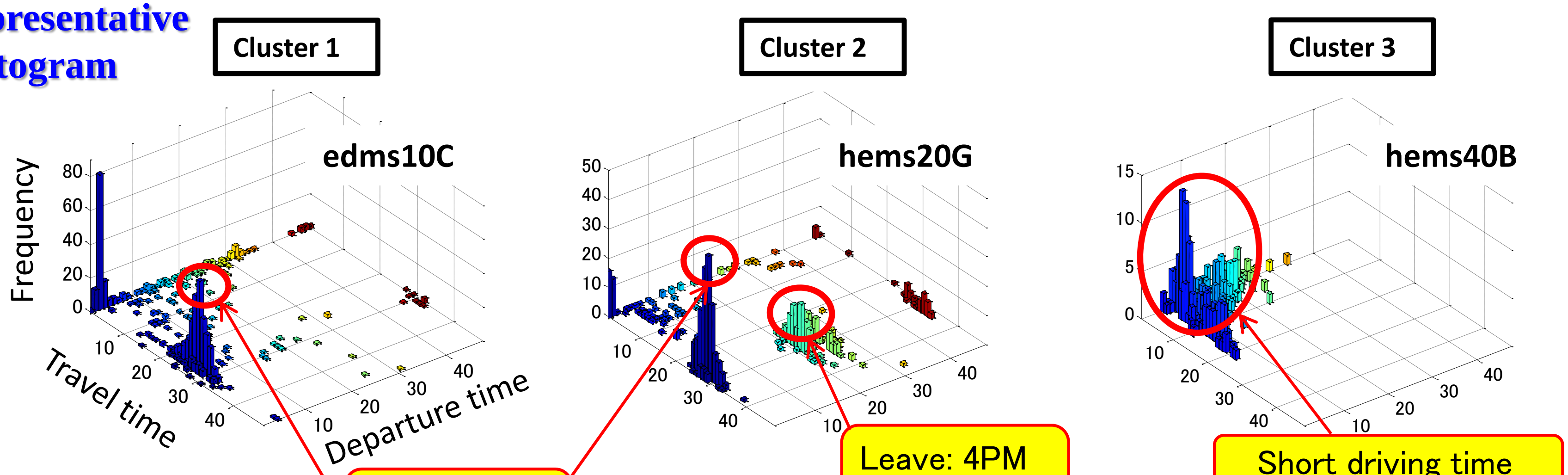




Clustering of Vehicle Use (Nov. 2012 – Jan. 2015: week day)



Representative Histogram



leave : 7AM
return : 7PM

Leave: 4PM
return : 2AM

Short driving time

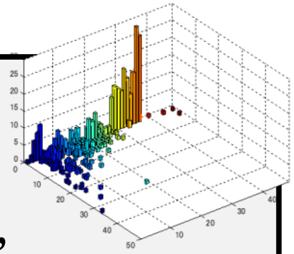
Prediction of Vehicle Use based on Dynamic Programming (1/3)

Predict the future Profile of Departure and Travel Time (PDTT)

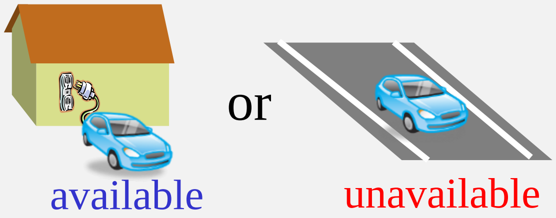
Given: s_0: Last departure time,

γ: The current state of the car,

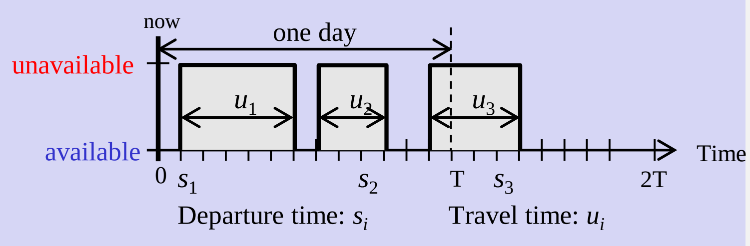
A : Statistics of Departure and Travel Time (SDTT),



Departure time s_i		1:00	1:30	2:00	⋯	0:30
step		1	2	3		48
Travel Time u_i [step]	0	30	24	15	⋯	33
	1	3	1	5	⋯	1
	2	6	4	2	⋯	2
	3	3	2	3	⋯	0
	⋯	⋯	⋯	⋯	⋯	⋯
	49	2	⋯	⋯	⋯	4



find: $(s_1,u_1), (s_2,u_2),\ldots, (s_k,u_k)$:Profile of Departure and Travel Time (PDTT)



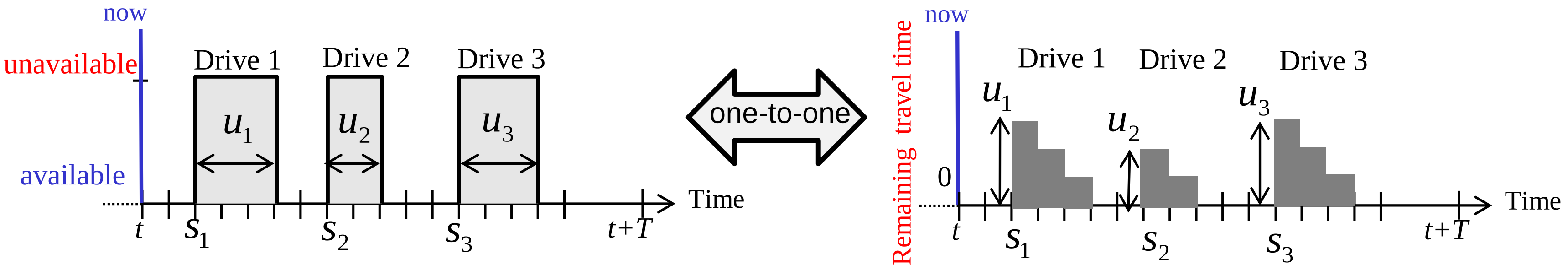
which maximizes:

$$J = P((S_1,U_1)=(s_1,u_1),(S_2,U_2)=(s_2,u_2),\cdots,(S_k,U_k)=(s_k,u_k)\,|\,s_0,\gamma)$$

:Occurrence probability (joint probability) of the PDTT

low computational cost algorithm must be developed for real-time implementation

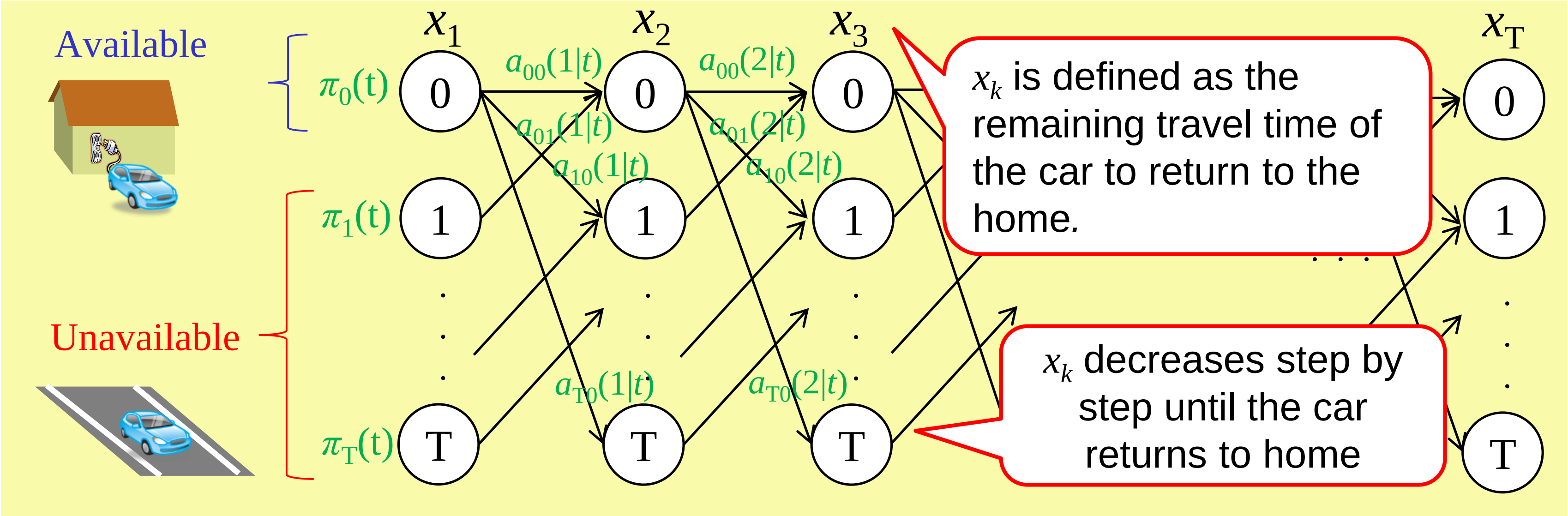
Prediction of Vehicle Use based on Dynamic Programming (2/3)



$(s_1,u_1), (s_2,u_2),\ldots, (s_k,u_k)$

$\mathbf{x}=\{x_1,x_2,\cdots,x_T\}, x_i\in\{0,1,\cdots,T\}$

Modeled by a semi-Markov model



x_k is defined as the remaining travel time of the car to return to the home.

x_k decreases step by step until the car returns to home

Prediction of Vehicle Use based on Dynamic Programming (3/3)

Predict the future Profile of Departure and Travel Time (PDTT)

which maximizes:

$$J = \underline{P((S_1,U_1)=(s_1,u_1),(S_2,U_2)=(s_2,u_2),\cdots,(S_k,U_k)=(s_k,u_k)\,|\,s_0,\gamma)}$$

Occurrence probability (joint probability) of the PDTT

Finding state sequence

$$\boxed{[x_t,\cdots,x_{t+T}]^* = \mathop{arg\,max}_{x_t;\cdots,x_{t+T}}\left[\pi_{x_t}(t)a_{x_tx_{t+1}}(t)\cdots a_{x_{t+T-1}x_{t+T}}(t+T-1)\right]}$$

Search on semi-Markov model → Dynamic programming

Score: $\delta_{t+k}(x_{t+k}) = \underline{\max_{x_t;\cdots x_{t+k}}\left\lfloor\pi_{x_t}(t)a_{x_tx_{t+1}}(t)\cdots a_{x_{t+k-1}x_{t+k}}(t+k-1)\right\rfloor}$

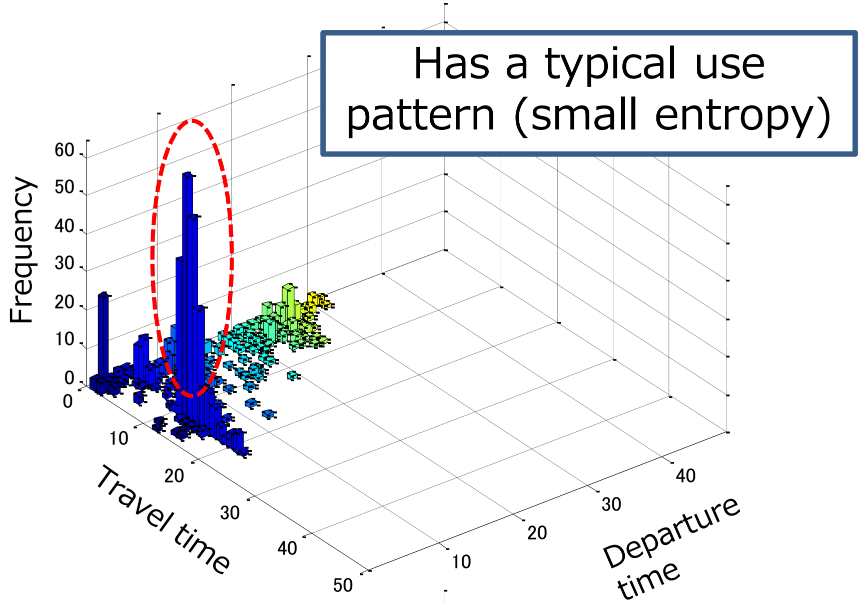
$\delta_{t+k}(x_{t+k})$ is a maximum likelihood over the possible state sequence from t to $t+k$

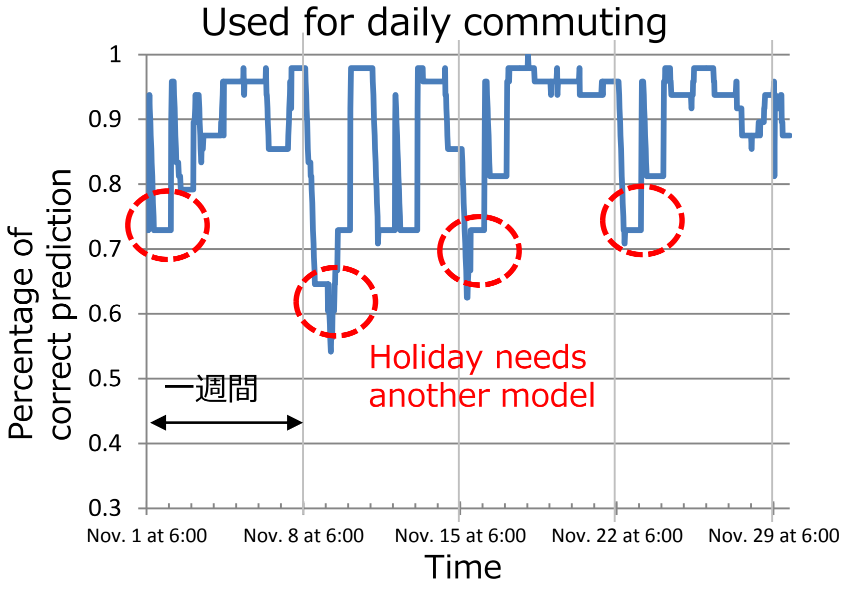
$$\delta_t(x_t)=\pi_{x_t},\quad \delta_\tau(x_\tau)=\max_{x_{\tau-1}}\left\lfloor\delta_{\tau-1}(x_{\tau-1})a_{x_{\tau-1}x_\tau}(\tau-1)\right\rfloor\ (t+1\le\tau\le t+T)$$

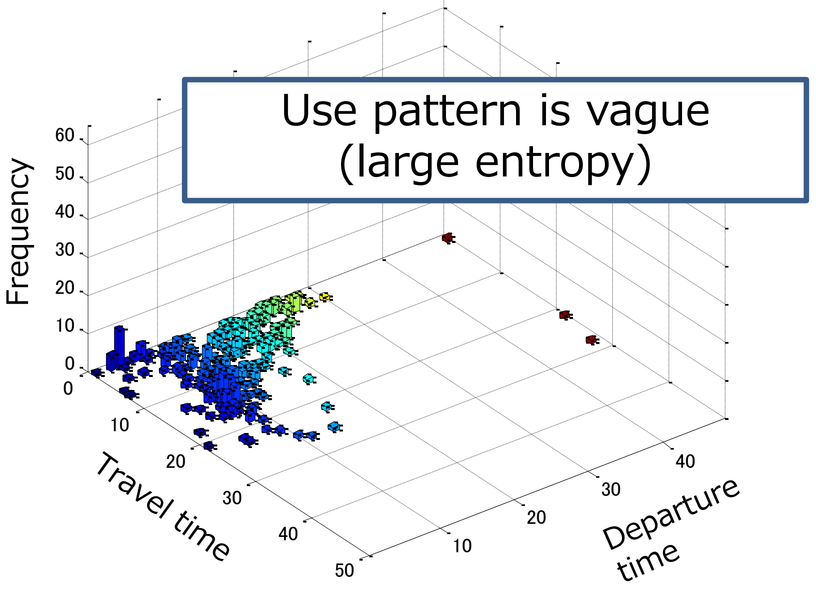
$$\boxed{J^* = \max_{x_{t+T}}\delta_{t+T}(x_{t+T})}$$

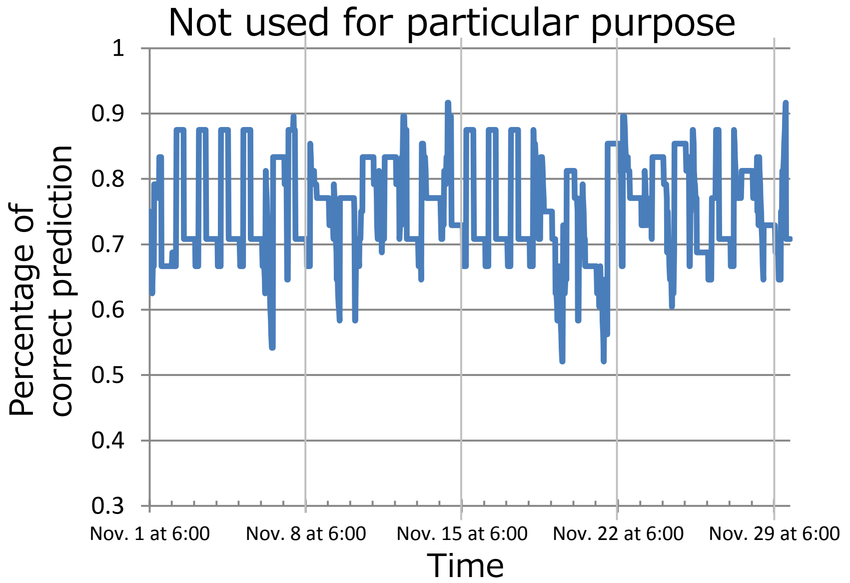
Computational cost is O(T^2)

Performance of prediction


Has a typical use pattern (small entropy)


Used for daily commuting


Use pattern is vague (large entropy)


Not used for particular purpose

Model predictive HEMS (V2H)

$h \in \{1, \cdots, H\}$

Given :

$\tilde{W}_h^+(k|t) \geq 0$ $\tilde{W}_h^-(k|t) \leq 0$: Consumed /Generated electricity in time $t+k$ predicted at t (kW)

$f^+(t) > 0$ $f^-(t) > 0$: Purchasing / selling price of electricity at t (JPY/kWh)

$\tilde{\gamma}_h(k|t) \in \{0,1\}$: Connected /disconnected state of the vehicle (0:connected, 1:disconnected)

$\tilde{B}_h^{cons}(k|t)$: Consumed electricity of the vehicle by driving (kWh)

$W_h^{\max}(k|t)$: Upper bound of net power dispatched from the aggregator (kW)

Find :

$$x_h^{POP}(t) = \{x_h^{POP}(1|t), x_h^{POP}(2|t), \cdots, x_h^{POP}(T|t)\}$$

SoC profile of the in-vehicle battery up to T steps (24h) ahead of time t (kW)

= POPs: preferred operating points

Subject to :

Continuous variable

Charging speed

Minimum SoC ....

Logical variable

Vehicle is connected or not

Prevention of backflow from battery:

$$\tilde{W}_h^+(k|t) + x_h^{POP}(k|t) - x_h^{POP}(k-1|t) \geq 0$$

Upper bound of net power:

$$\tilde{W}_h(k|t) \leq W_h^{\max}(k|t)$$

Models of PCS and batteries

Which minimize :

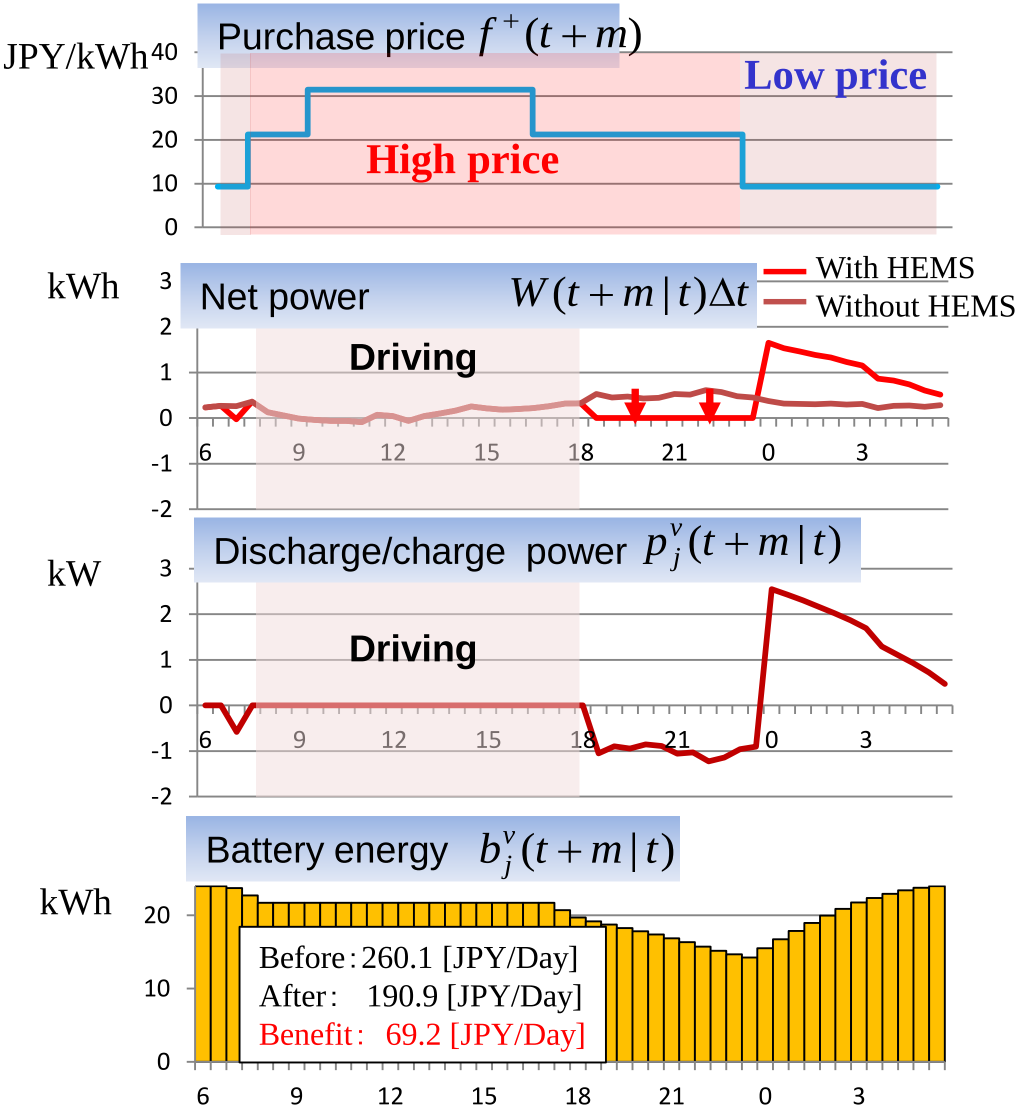
$$Z_h(t) = \underbrace{\sum_{k=1}^{T} F(t+k)\tilde{W}_h(k|t)\Delta t}_{\text{Electricity fee for 24hours}} + \alpha \underbrace{\sum_{k=1}^{T-1} D_h(k|t)}_{\text{Number of charge/ discharge}}$$

$$F(t+k) = \begin{cases} f^+(t+k) & \text{if } \tilde{W}_h(k|t) \geq 0 & \text{(Purchase)} \\ f^-(t+k) & otherwise & \text{(Sale)} \end{cases}$$

$$\underbrace{\tilde{W}_h(k|t)}_{\text{Net power}} = \tilde{W}_h^+(k|t) + \tilde{W}_h^-(k|t) + x_h^{POP}(k|t) - x_h^{POP}(k-1|t)$$

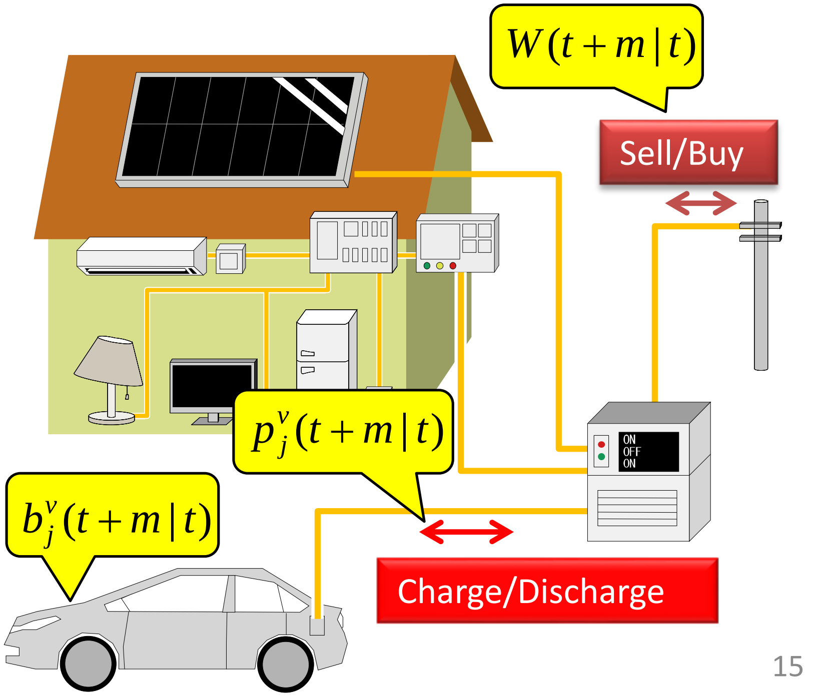
Simulation results I

Consumed power, generated power and profile of car use are assumed to be known.



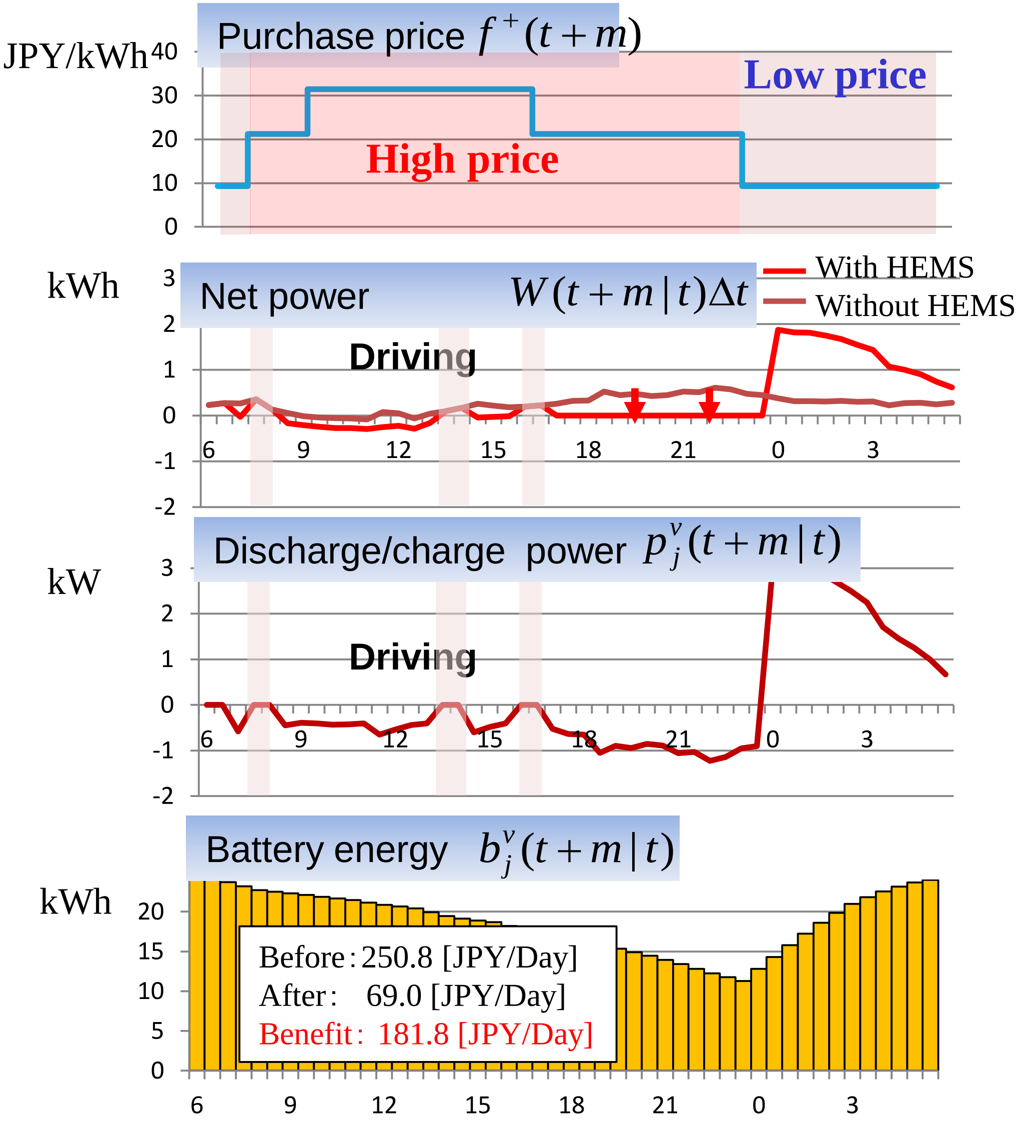
Before : 260.1 [JPY/Day]
After : 190.9 [JPY/Day]
Benefit : 69.2 [JPY/Day]

- PHV is not used as the power storage in the HEMS while it is not connected to the home.
- The HEMS can decrease the purchased electric power in the high price time zone.



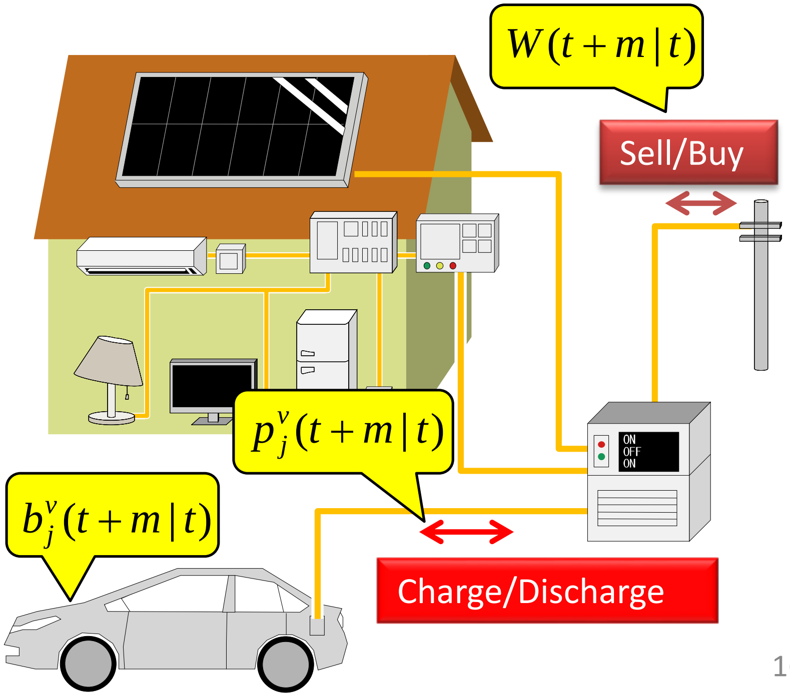
Simulation results II

Consumed power, generated power and profile of car use are assumed to be known.



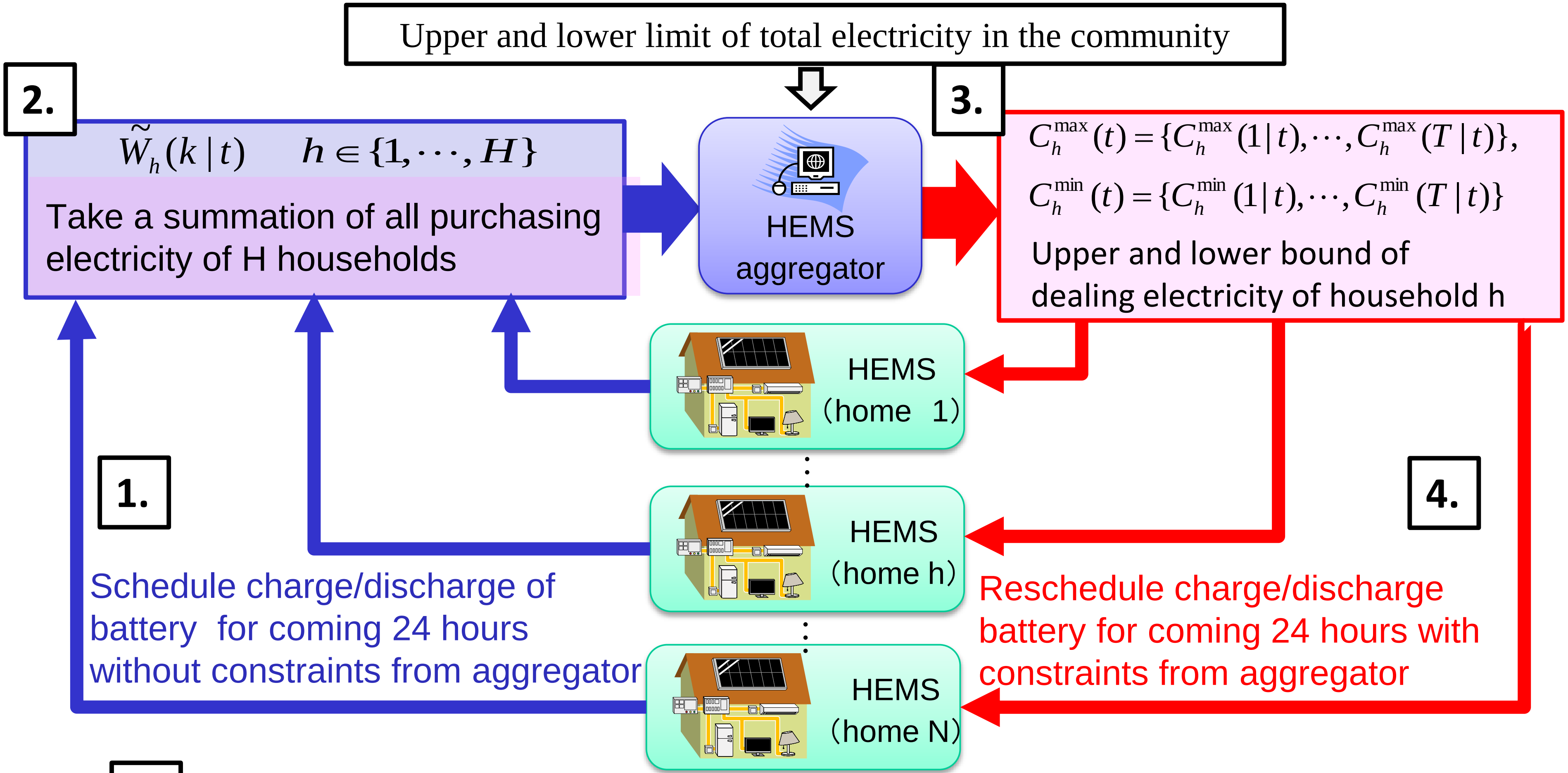
Before : 250.8 [JPY/Day]
After : 69.0 [JPY/Day]
Benefit : 181.8 [JPY/Day]

- EV is not used as the power storage in the HEMS while it is not connected to the home.
- The HEMS can decrease the purchased electric power in the high price time zone.



HEMS aggregator specifying constraints on each HEMS

The role of HEMS aggregator is to decide the constraints of dealing electricity at each household so as to satisfy the supply demand balancing in real-time



Upper and lower limit of total electricity in the community

2.

$\tilde{W}_h(k\,|\,t) \qquad h \in \{1,\cdots,H\}$

Take a summation of all purchasing electricity of H households

HEMS aggregator

3.

$C_h^{\max}(t) = \{C_h^{\max}(1\,|\,t),\cdots,C_h^{\max}(T\,|\,t)\},$

$C_h^{\min}(t) = \{C_h^{\min}(1\,|\,t),\cdots,C_h^{\min}(T\,|\,t)\}$

Upper and lower bound of dealing electricity of household h

1.

Schedule charge/discharge of battery for coming 24 hours without constraints from aggregator

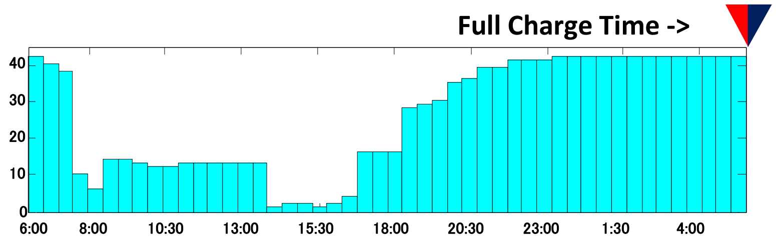
4.

Reschedule charge/discharge battery for coming 24 hours with constraints from aggregator

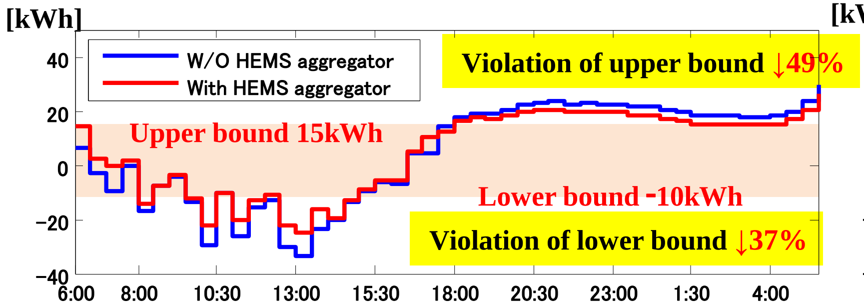
5. Operate the rescheduled charge/discharge plan for 30 min. (control period: 30 min.)

HEMS aggregator specifying constraints on each HEMS (Results)

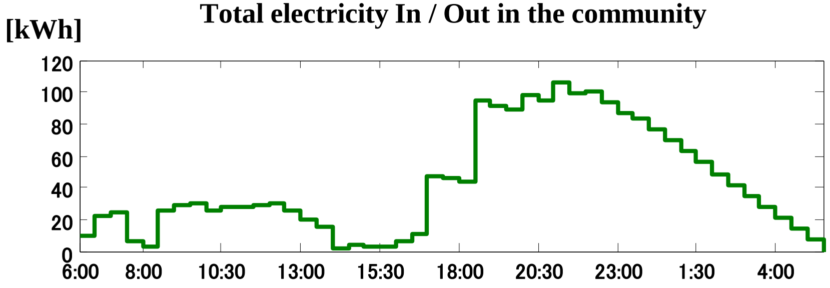
Case 1 Available Vehicles — Day time : Night time 2 : 1



Number of vehicles available in HEMS

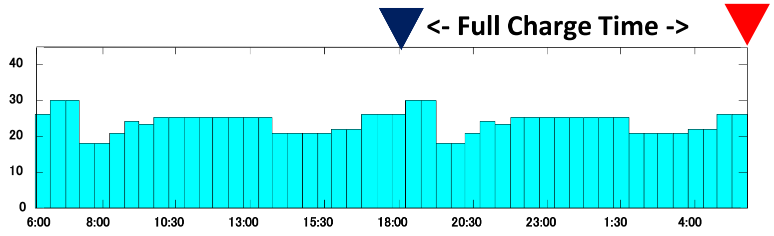


Total electricity In / Out in the community

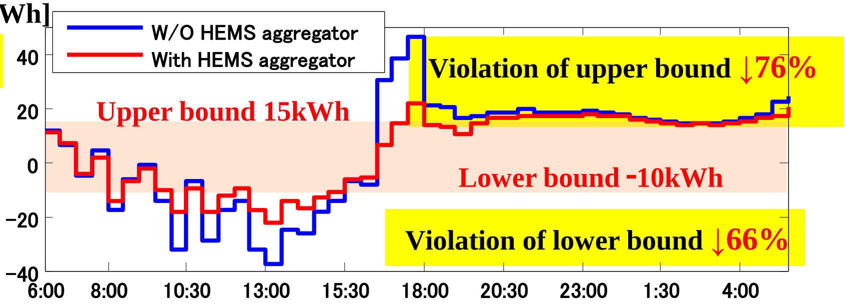


Total free capacity of batteries in the community

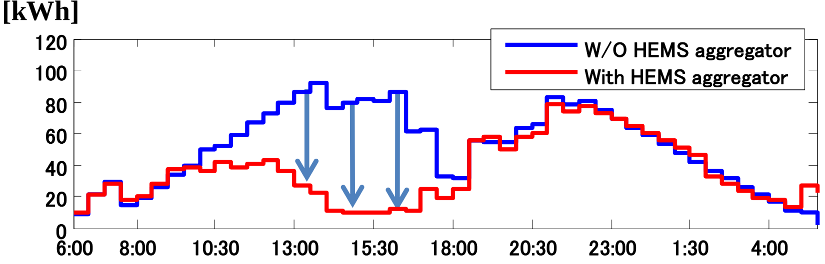
Case 2 Available Vehicles — Day time : Night time 1 : 1



Number of vehicles available in HEMS



Total electricity In / Out in the community



Total free capacity of batteries in the community

Increase the effectiveness with the total free capacity of in-vehicle batteries by variety of vehicle use profiles.

CREST project (from April 2015)

Integrated Design of Local EMSs and their Aggregation Scenario Considering Energy Consumption Behaviors and Cooperative Use of Decentralized In-Vehicle Batteries

Primary Collaborators		
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H. Ishii（Tokyo Inst. of Tech.）	T. Onoda（CRIEPI）	

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W. Kempton（Univ. of Delaware）


Suzuki


Ito


Baba


Fujimoto


Susuki


Ishii


Onoda


Kempton

Discussion

Thank you
for your attention