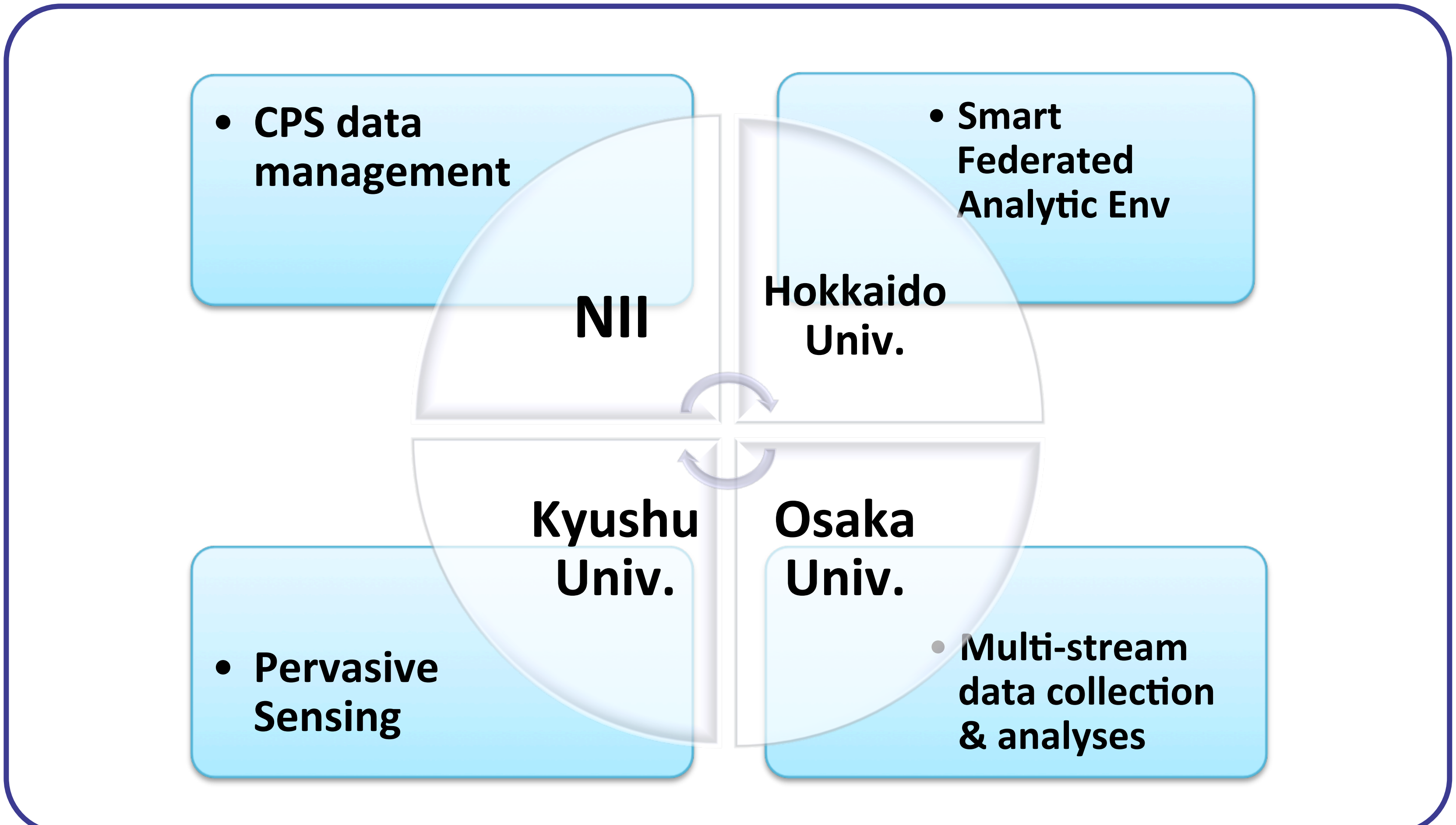
Recent Research for Social CPS in Japan

Teruo Higashino (Osaka Univ., JP)
and Rin-ichiro Taniguchi (Kyusyu Univ., JP)

CPS-IIP: Integrated IT Platforms for Cyber-Physical Systems to Accelerate Implementation of Efficient Social Systems

September 2012 -- March 2017 funded by MEXT



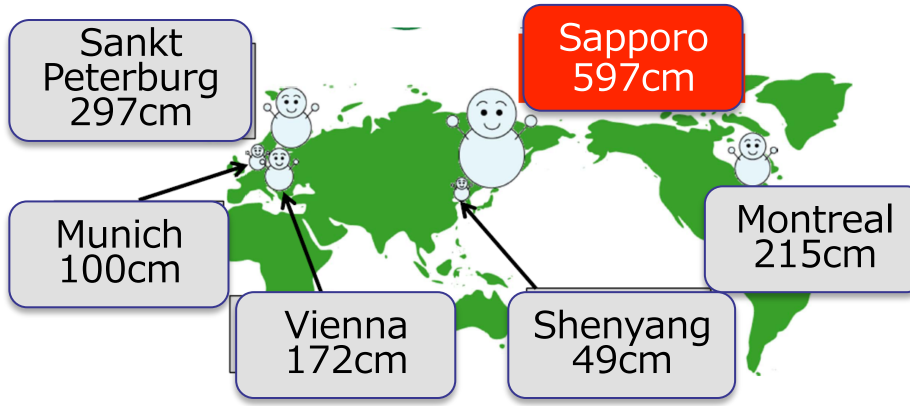
Several Service Applications are considered in CPS-IIP Project

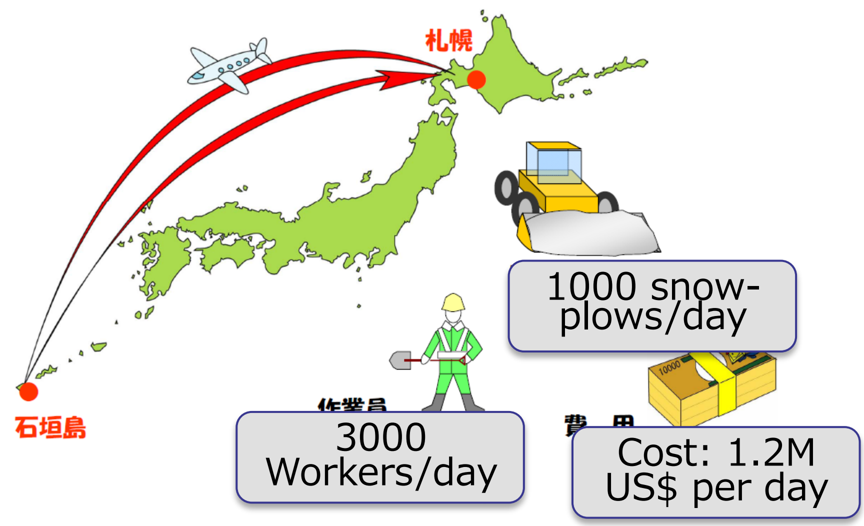
- Efficient Snow Plowing in a Large City
  - Sapporo City's Snow Plowing
- CPS based ITS Research
  - Travel Time Estimation in Snowfall Conditions
  - Real-Time Traffic Incident Detection System in Tokyo
- Disaster Management
  - Crowd Sensing based Disaster Management
- Crowd Sensing in Urban Areas
  - Pedestrian Mobility Estimation
- Human Centric BEMS on Commercial Buildings & University Campus
  - Human Centric BEMS using Crowd Sensing Data
  - Smart Campus with CPS

Efficient Snow Plowing in Sapporo City

Snow Plowing in Sapporo City

- Population: 1,920,739
- Annual snowfall: 597cm
  - The most snowy city in the world among the cities with more than 1M population
- Annual budget for snow plowing and removing (2010)
  - 14,729,000,000 yen
  - (147,000,000 US$/year)
  - Winter in 2014:
  - 22,000,000,000 yen
  - (220,000,000 US$/year)
- Total distance of snow plowing and removing during one night:
  - 5,328km





Goals

Improvement on

- Average speed of the traffic
- Average delay of fixed route buses
- Average arrival time of emergency vehicles
- CO_2 emission from traffic jams
- Annual cost of snow removal
- Winter traffic accidents

Evidence-based quantitative account on

- Traffic disturbance by snowfalls
- Snow removal effect
- Traffic accidents caused by frozen roads

Information sharing between the city government and citizens

Citizen → Government

Hearing of opinions

- Complaints
- Report on road conditions and accidents

Local Government → Citizens

Visual Information services

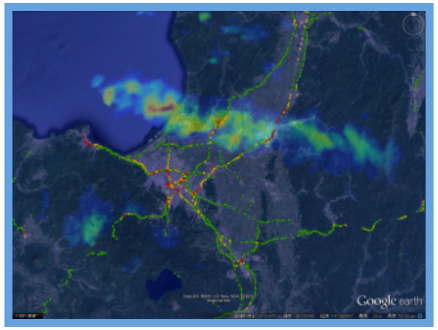
- Road conditions
- Traffic conditions
- Snow removal conditions
- Weather conditions

Preparation of Data and Real-time Monitoring

OSAKA UNIVERSITY

- **Traffic Data**
  - Probe-car data: private cars (past 3 yrs) & taxis (past 3 yrs + real-time: at every 5 min.) & 23 buses (real-time)
  - ABS activation location data
  - Traffic jam sensor data (past 2 yrs)
  - Statistical subway passenger records (past 9 yrs)

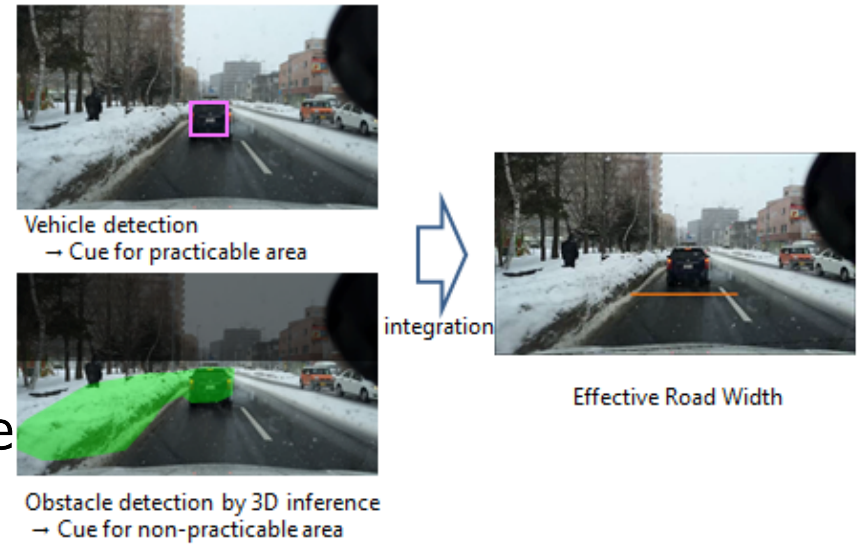
- **Weather Data**
  - Meteorological multi-sensor data (52 locations) (past 10 yrs +realtime data)
  - Weather mesh data
  - X band MP radar data (realtime: at every 5 min.)



3D Road Measurement by Bus with Laser Range Scanner

Road Measurement

- **Monitoring and estimating effective road width**
  - Approximate estimation from 3D measurement data
  - Estimation from real time probe car data
  - Estimation from road images
- **Estimating the amount of removing snow**
  - Approximate estimation from 3D measurement



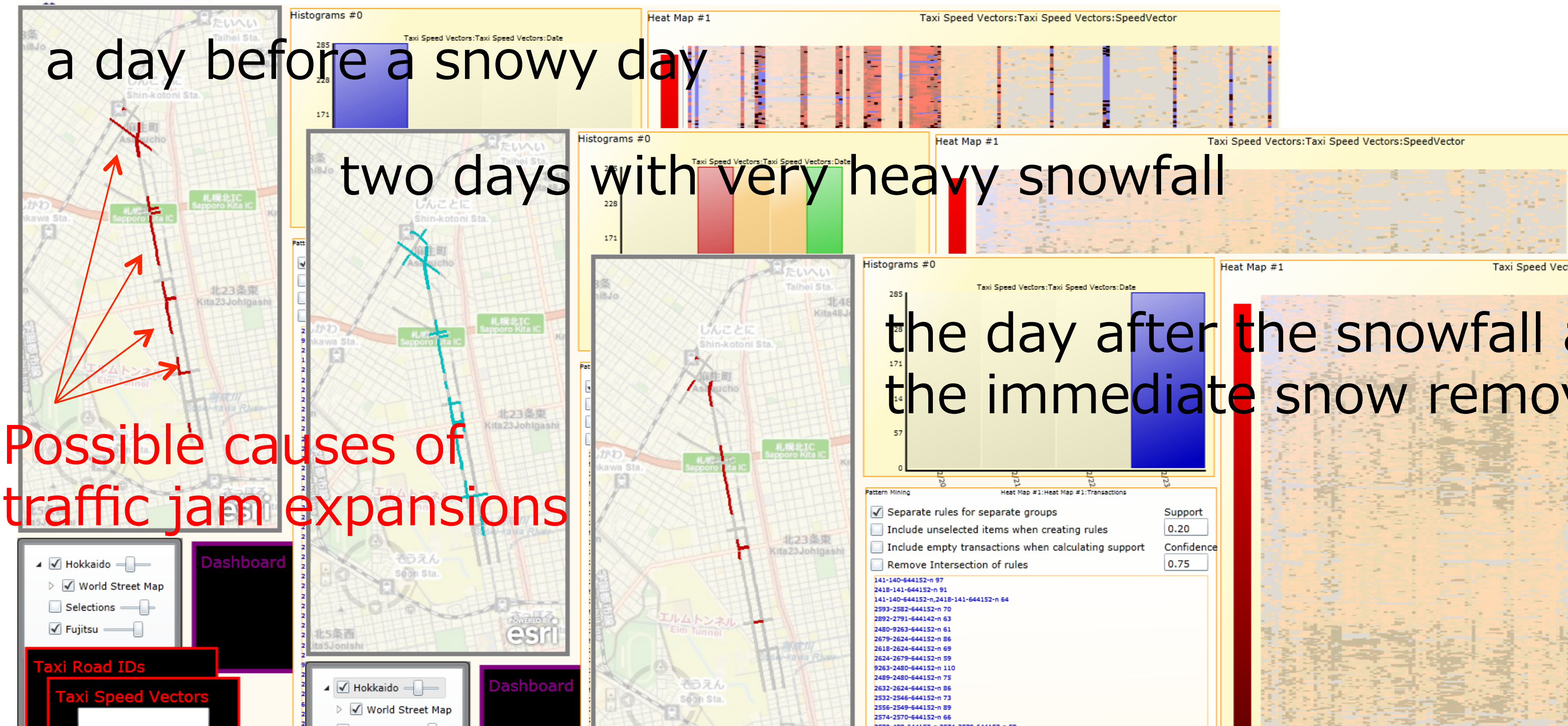
Estimating the amount of snow removal from 3D measurement data

Detecting Pinpoint Snow Removal Areas

- A heavy snowfall may expand a traffic jam localized in a single road link to its adjacent road links.
- Traffic obstacles cause unexpected traffic jum
  - illegally parked cars
  - places where snow drifts (natural/artificial)
- Identification of the locations of snow drifts and illegally parked cars

- Pinpoint snow removal and pinpoint crackdown of illegal parking are very important

Detecting Pinpoint Snow Removal Areas



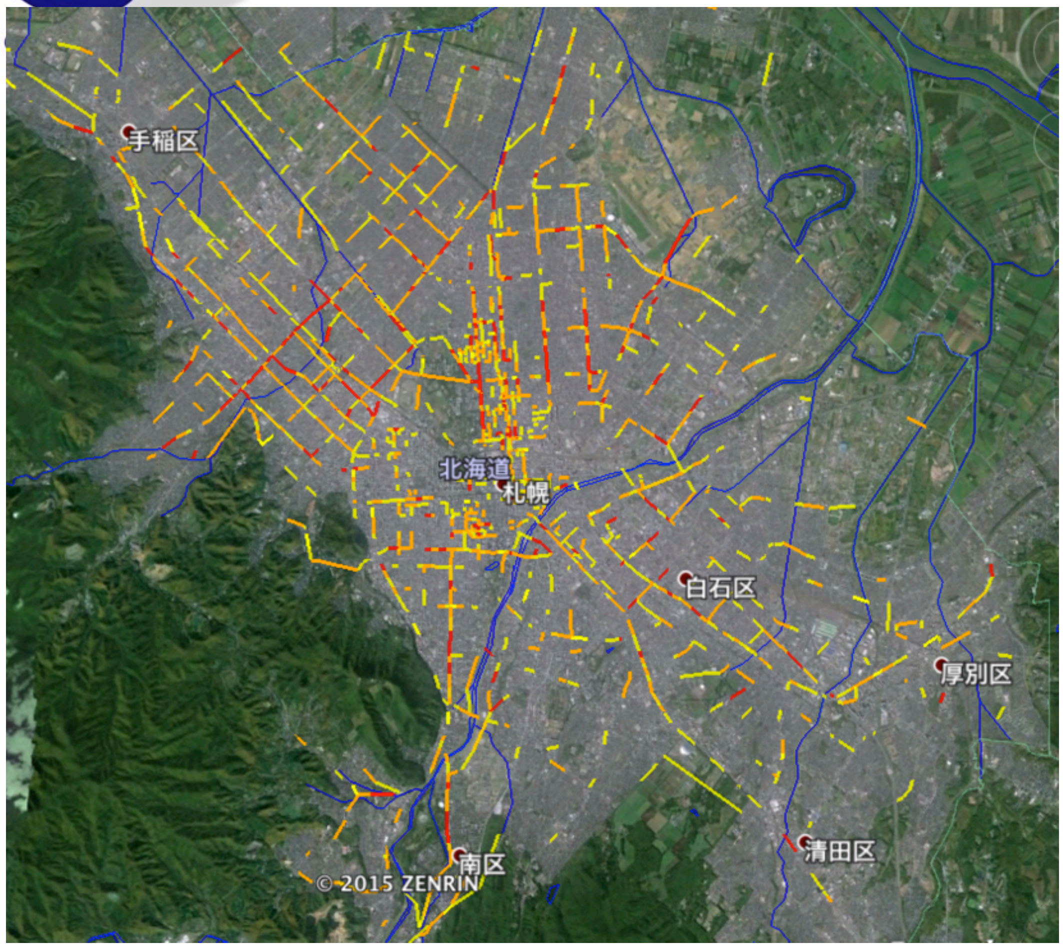
The traffic jam sections become seriously extended by the snowfall, and this situation significantly improves after the snow removal.

Travel Time Estimation in Winter

OSAKA UNIVERSITY

- In Sapporo City, it is rather difficult for drivers to estimate the travel time from their home to offices in winter
- In summer, even if it takes only 30 minutes to reach their offices, it might take 60 or 90 minutes in winter depending on snowy weather conditions
- People really want to accurately estimate the travel time from their home to offices before they leave their home
- For given weather conditions (snow depth, new snowfall, snow depth one day before, highest temperature one day before, speed in summer, speed drop one day before, etc.), we propose a method to estimate the travel time for target road segments
- It does not consider sudden traffic accidents and special road situations

Correlation between Snowfall and Speed Drop



Correlation Coefficient	
red	Corr.>**0.7**
orange	0.7>Corr.>**0.6**
yellow-green	**-0.5>Corr.**

Weak Correlation
- low traffic

Strong Correlation
- Main roads with >=2 lanes

Construct a speed model for main roads in snowfall situations

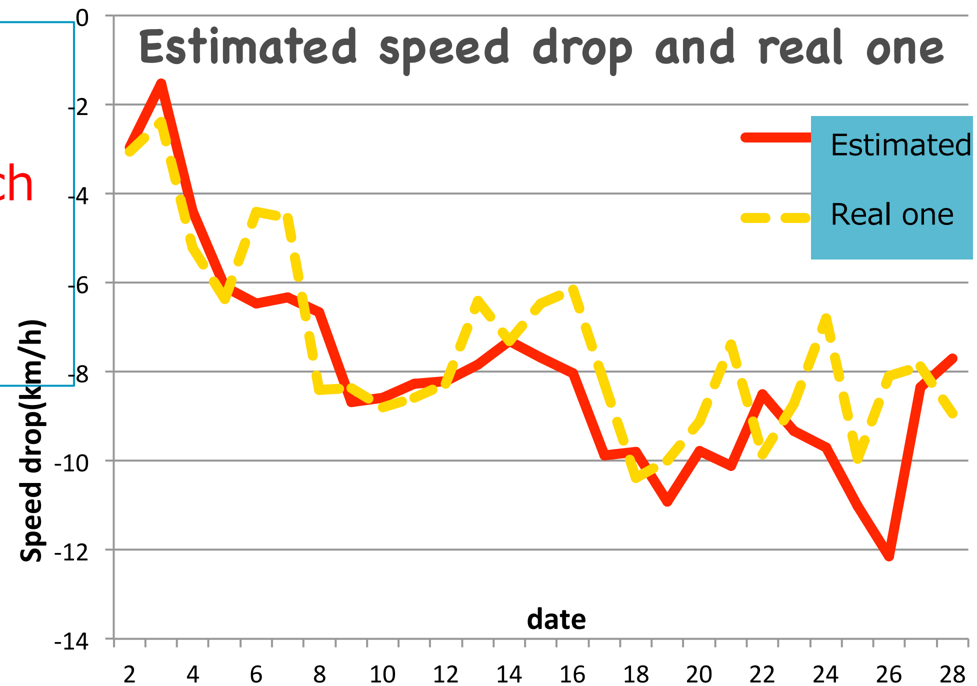
✓ We are studying the correlation between snowfall and speed drop in Sapporo

Multiple Regression Analysis

OSAKA UNIVERSITY

Multiple Correlation :
0.844 (R^2 = 0.713)

We construct a speed model for each road segment in order to estimate average speed drop for each target date and weather



Parameters

	coefficient	t-value
Initial value	+8.071	+6.10
Snow depth(cm)	-0.0470	-4.63
New snowfall(cm)	-0.0453	-2.49
Snow depth one day before(cm)	-0.0539	-3.09
Highest temp. one day before(℃)	+0.207	+4.39
Speed in summer(km/h)	-0.202	-6.99
Speed drop one day before(km/h)	+0.632	+19.77

New Snowfall
→Speed is decreased

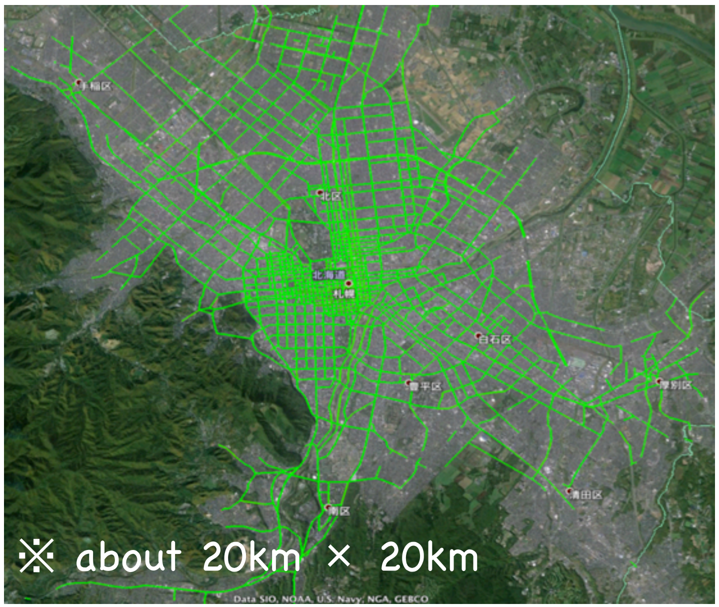
Temperature one day before is high
→Speed is increased

Today's Speed Drop (km/h) = Initial value + ○○ × Snow depth + △△ × New snowfall + □□ × Speed drop one day before + ……

Evaluation: Speed Prediction

OSAKA UNIVERSITY

- System evaluation using real data in Sapporo (Feb. 2013)
- Making the model and prediction for 7289 road segments



Situation	
Roads	The road segment that floating car data can be collected every day **7289** segments
Traffic data	FUJITSU SPATIOUL ※ commercial floating car data
Weather Info.	Japan Meteorological Agency
Model making	01.Feb.2013 ~ **21**.Feb. (21days)
Prediction	**22.**Feb.2013 ~ 28.Feb. (7days)

① Multiple Regression Analysis

Speed Model ×7289

01.Feb.~ 21.Feb.

Speed =	-0.30 × Depth
	-0.15 × Fall
	+0.50 × Temp+10.0

② Predict Speed

	Predict	Real	Error
2/22	**-8.0**km/h	**-7.5**km/h	0.5
…	…	…	…
2/28	**-5.0**km/h	**-4.0**km/h	1.0

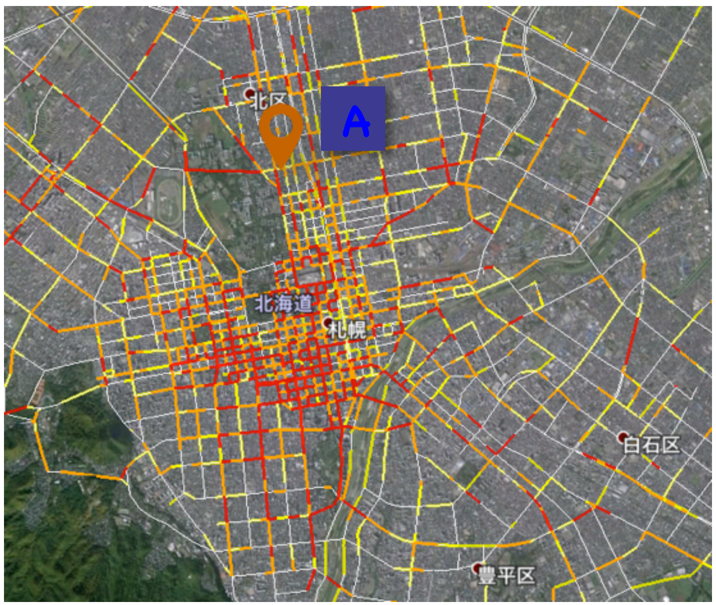
③ Evaluation

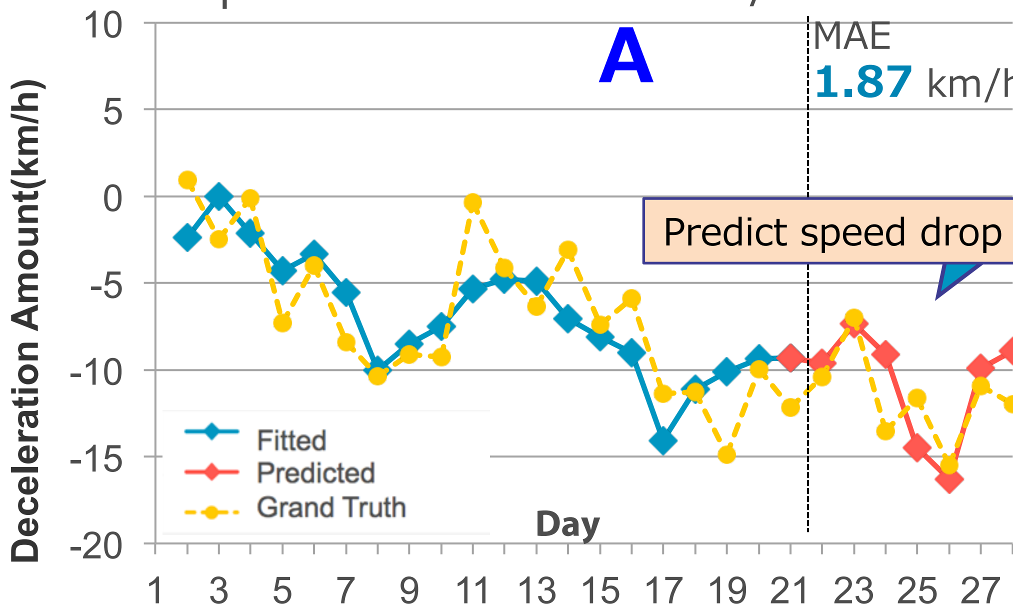
Calculate Mean Absolute Error

Road A: Main Road from Suburb to City Center

OSAKA UNIVERSITY

- Using speed model, the major factors of speed in road A are estimated
- The speed drops of one week later are predicted with 1.87km/h errors





Road A
The speed deceleration is large and the major factors are related to snow depth & snowfall

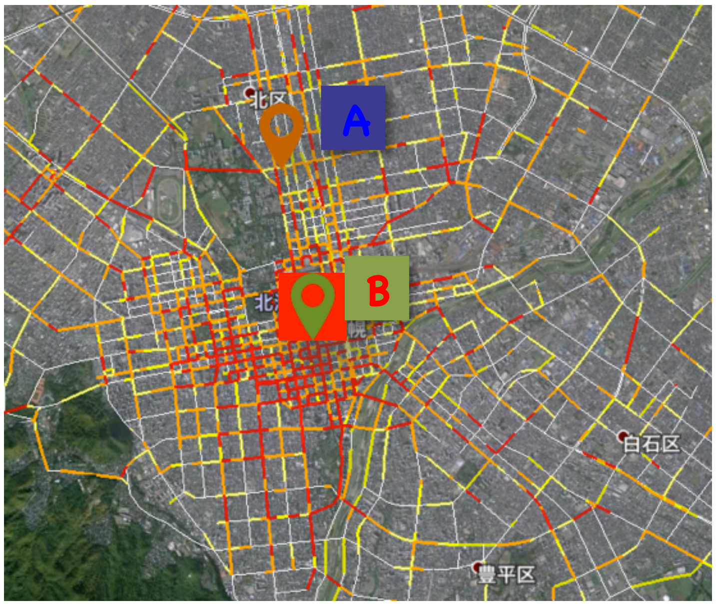
Speed Drop = **-0.20** × Snow Depth
-0.16 × Snowfall (Pre)
+14.35 (constant term)

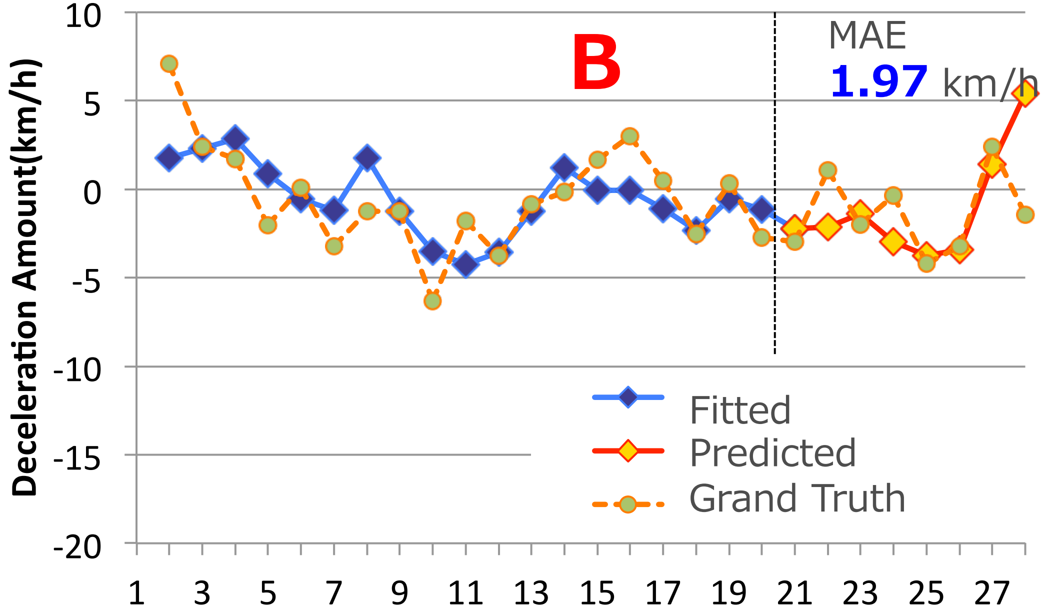
Snow amount ↑ → Vehicle speed ↓

Correlation **0.797**

Road B: Road in City Center

- In road B, the speed deceleration is relatively small
- The weights for snow depth and snowfall are rather small





Road B
The speed deceleration is relatively small, since it is in the center of the city and crowded

Speed Drop = **-0.008** × Snow Depth
+0.85 × Min. Temp.
+0.31 × Speed(Pre)
+7.14(constant term)

Correlation **0.683**

Crowd Sensing based Disaster Management

Safety Management in Urban Districts

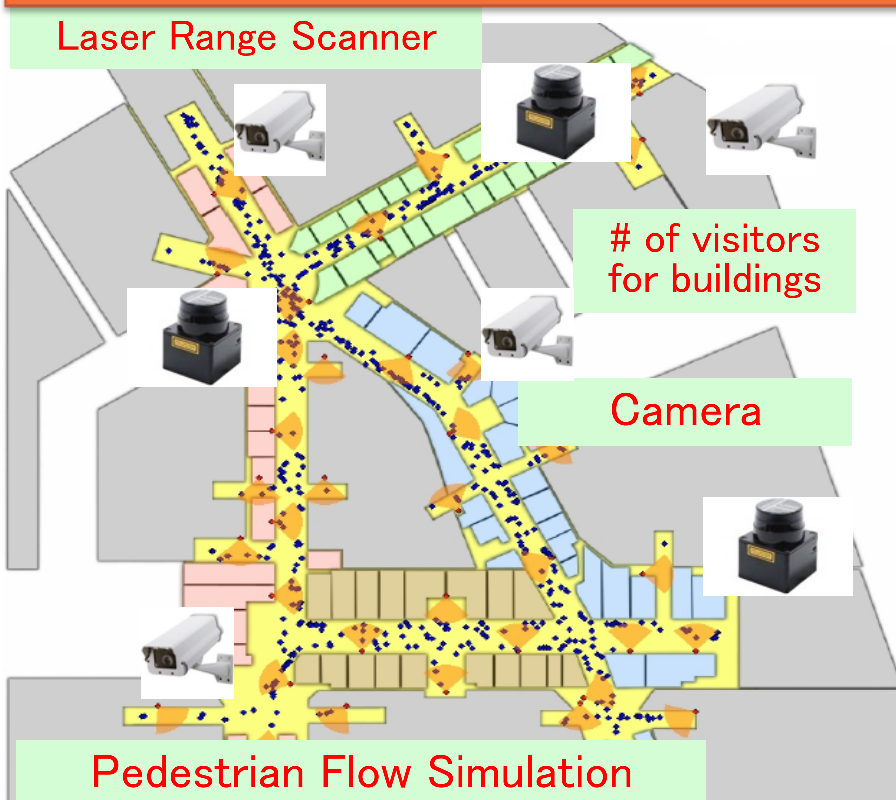
- ✧ A small fire occurred at underground Metro Osaka station in 2012 where a very small area in a warehouse under the platform is burned due to electric leak.
- ✧ 17 persons were conveyed to hospitals by ambulances. More than 3,000 people tried to refuge on the ground from underground. They could not find where the fire occurred and which directions they should run away.
- ✧ The number of pedestrians varies depending on weekday or weekend, and rush hour or daytime.
- ✧ Up-to-date crowd control at large stations, shopping malls and underground malls are very important for disaster mitigation.

Our Research Aim

OSAKA UNIVERSITY

- Our aim is to precisely estimate the up-to-date (real-time) population distribution and mobility patterns of crowd in urban districts and to apply the obtained knowledge to disaster mitigation and rescue support.

Urban Sensing/Simulation Technology



Disaster Mitigation & Rescue Support

3D visualization of crowd and synthesizing disaster mobility

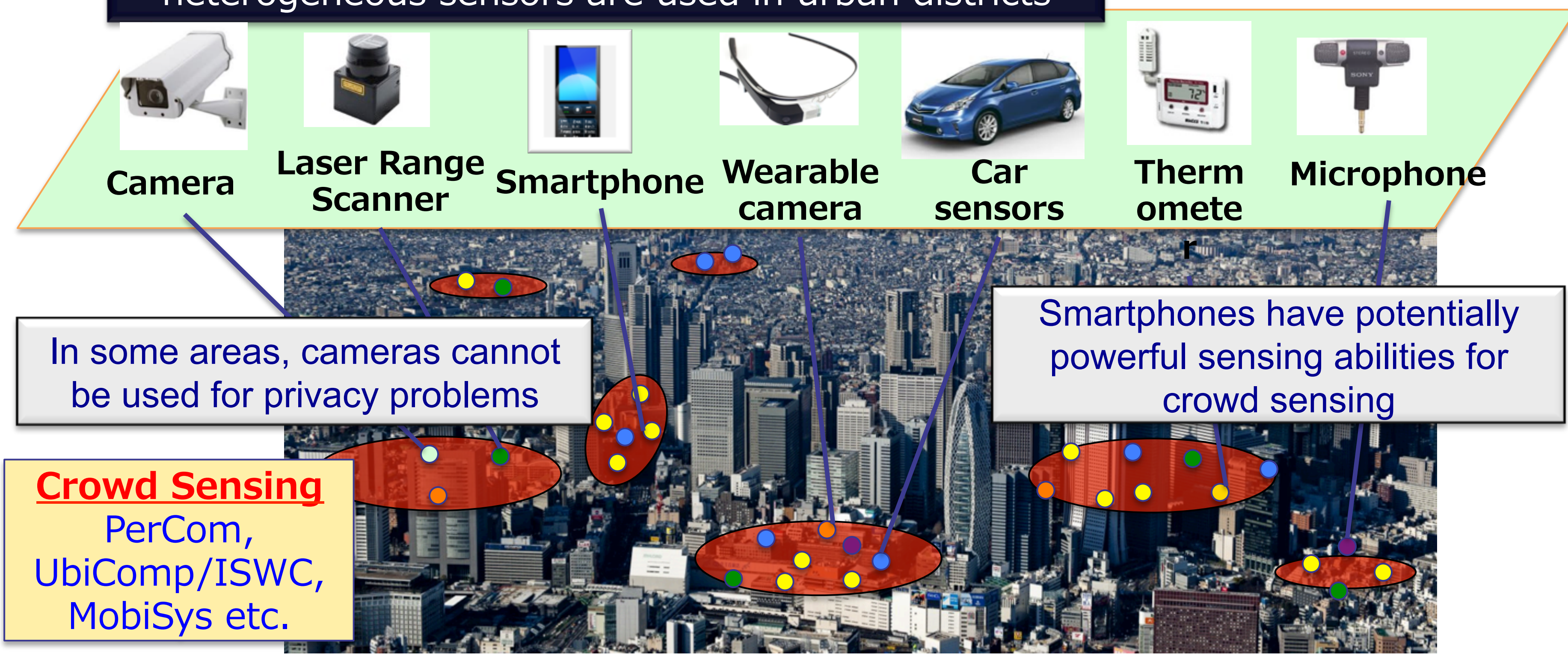
Estimation of Pedestrian flows

- Pedestrian distributions are not uniform
- From sensing results (crowd densities) at multiple observation points, we synthesize pedestrian flows in urban districts

Ad Hoc Networks, Vol.7-1

Synthesize

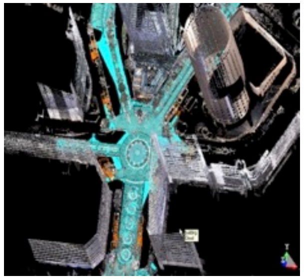
In order to synthesize pedestrian/vehicular mobility, heterogeneous sensors are used in urban districts



Crowd Sensing
PerCom,
UbiComp/ISWC,
MobiSys etc.

3D visualization for evacuation planning at underground malls

OSAKA UNIVERSITY



- We reproduce passages, add normal & emergency pedestrian flows and check efficiency of evacuation plans on 3D map so that local governments can make efficient evacuation plans. (e.g., evacuation planning for fire and flooding of target underground malls)
- Depending on date/time and real-time situations of disaster victims, we provide suitable evacuation routes and disaster information to their smartphones.

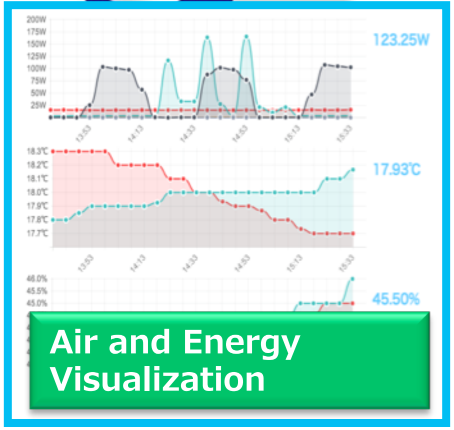
Visualize crowd mobility using AR technology

OSAKA UNIVERSITY

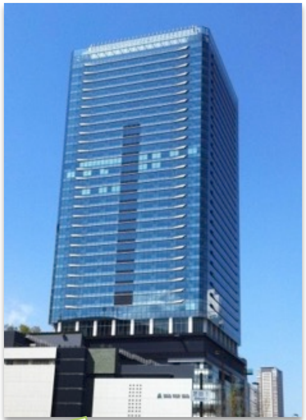
Crowd Sensing in Commercial Buildings

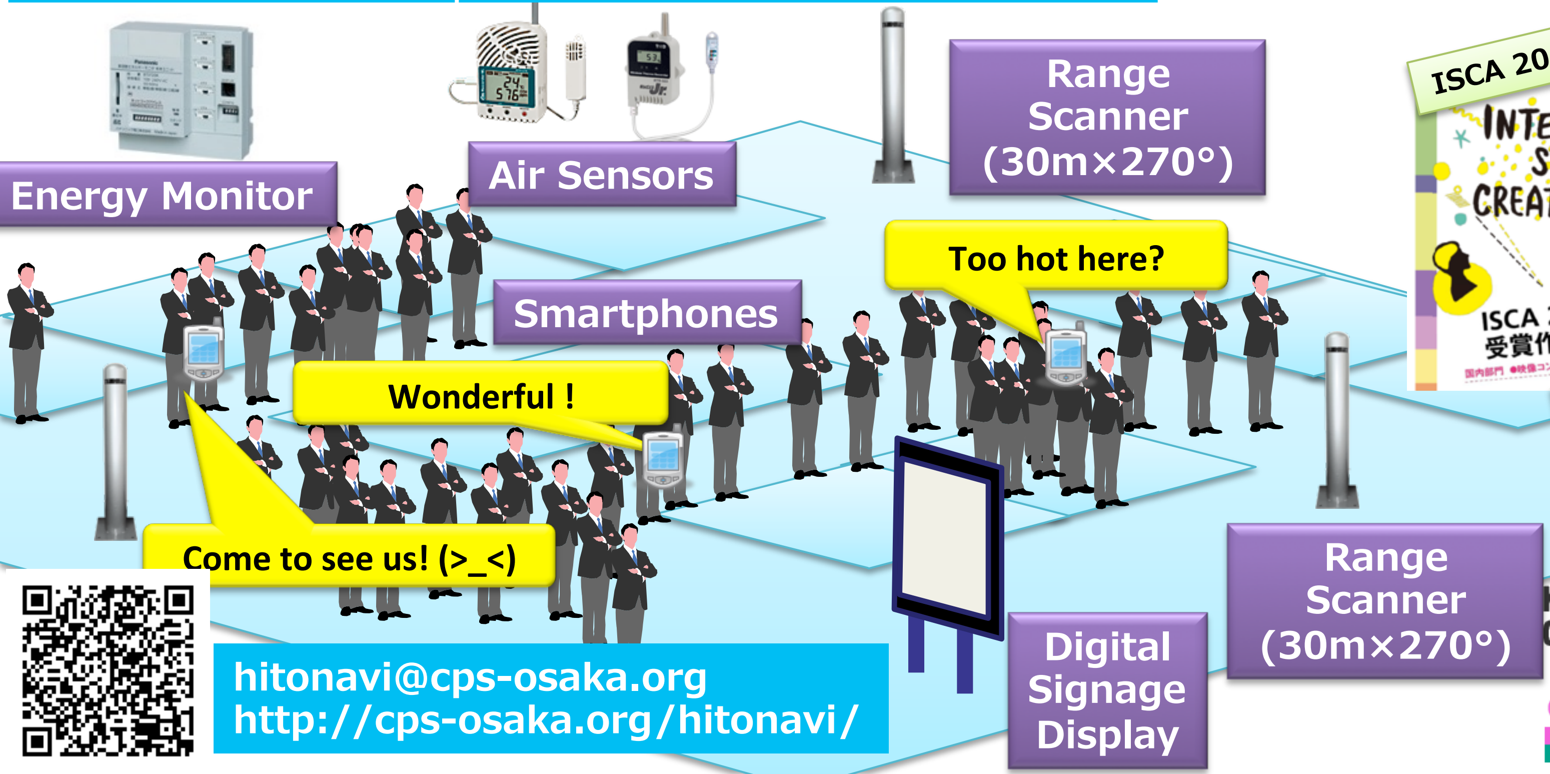
Hitonavi (Advanced Crowd Tracking System using LRS)

Location-based SNS | Crowd Navigation | Building Energy Management | Digital Signage | Behavior Analysis | Human BigData Analysis



"The Lab" in Grandfront Osaka (since Apr. 2013)





hitonavi@cps-osaka.org
http://cps-osaka.org/hitonavi/

KNOWLEDGE CAPITAL

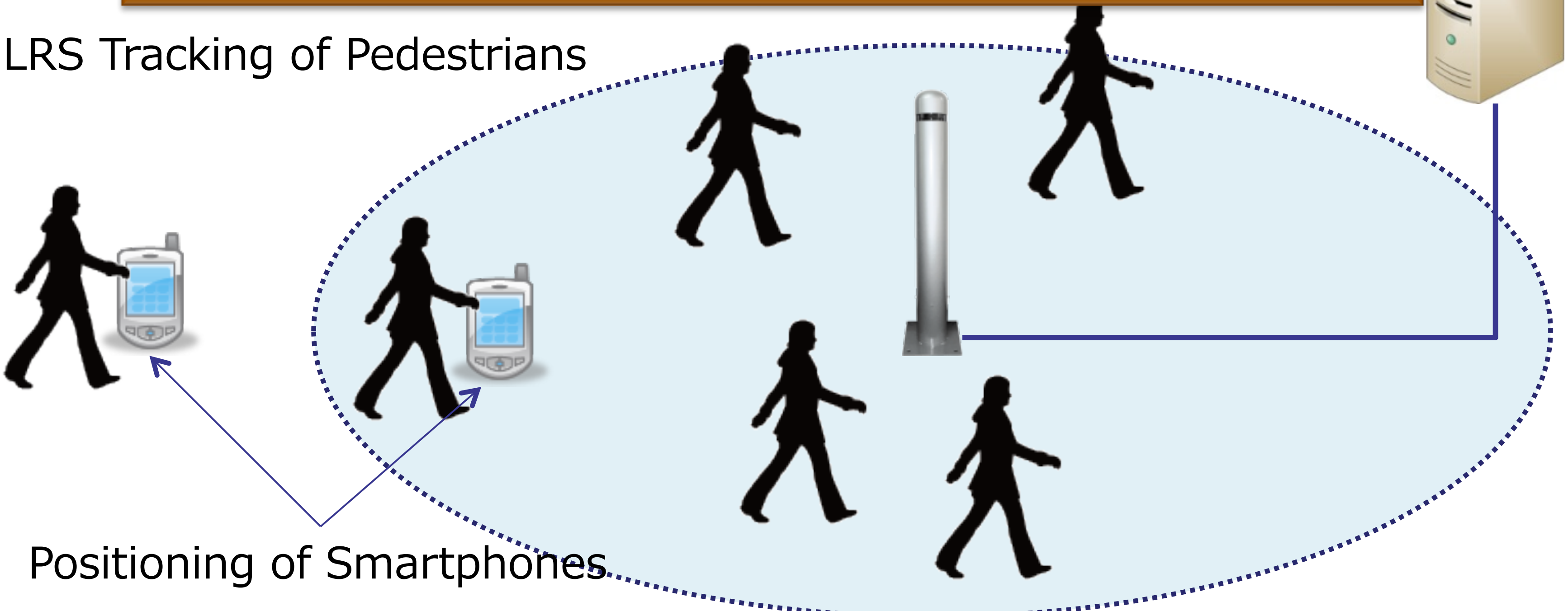
大阪大学 OSAKA UNIVERSITY

Crowd Tracking System “Hitonabi” at “The Lab” in Grand Front Osaka

The Lab. is a showcase (about 900 m^2 (30m*30m))

Tracking vs. Positioning

[○] Accurate
[○] Can track all the people without phones
[X] not applicable to LBS (Location Based Services)



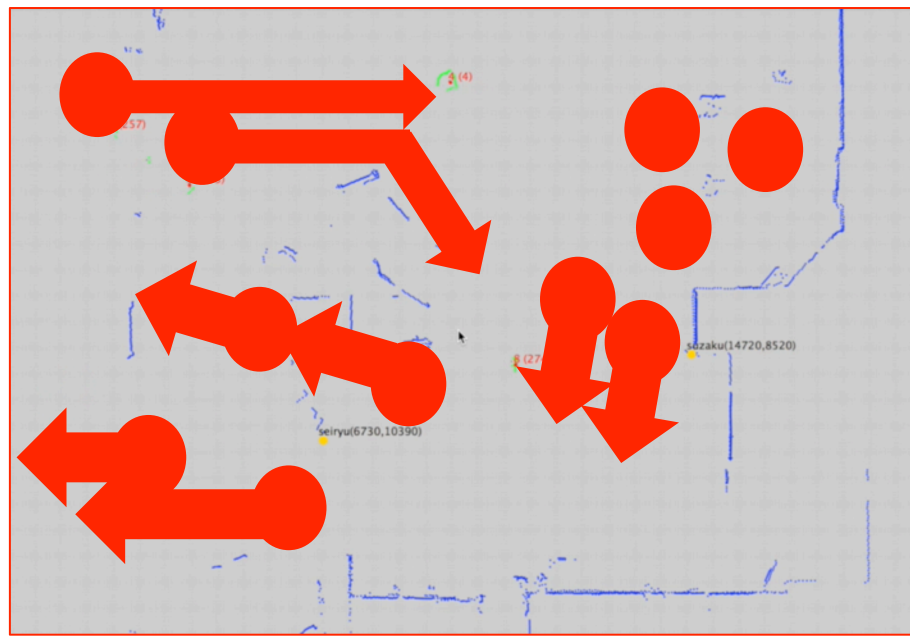
[X] often inaccurate （tens of meters errors in WiFi localization)
[X] positions of surrounding peoples are unknown (crowd etc)
[○] available for LBS (Location Based Services)

Accurate Positioning and Human Tracking by LRS & Smartphones

- find best matching between smartphones' motion information (from inertial sensors) and LRS trajectories to identify the highly accurate trajectories' owners

turned

walking straightly   stop and go



Locations of Your Own and Your Neighbors

OSAKA UNIVERSITY

Human-Centric BEMS using Crowd Sensing Data

Challenges for Human Centric BEMS

- Comfortable, energy-efficient air quality and HVAC (Heating, Ventilation, and Air Conditioning) management is still challenging
- This is due to lack of
  - concept of sensing and leveraging human locations and finer-grained environmental parameters (pinpoint temperature etc.)
  - understanding of human thermal comfort and feedback effect in HVAC control

Energy Reduction using IT

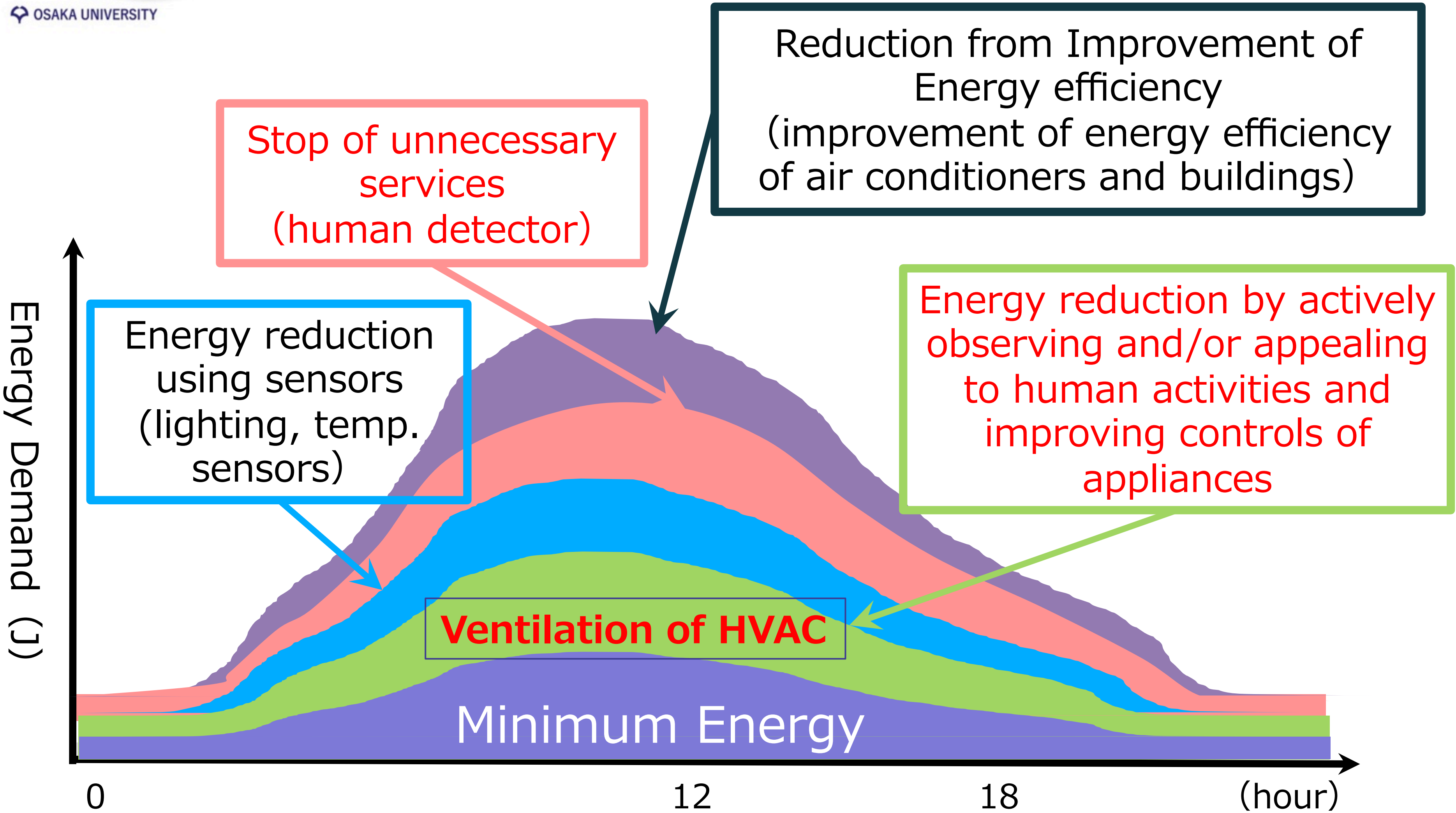
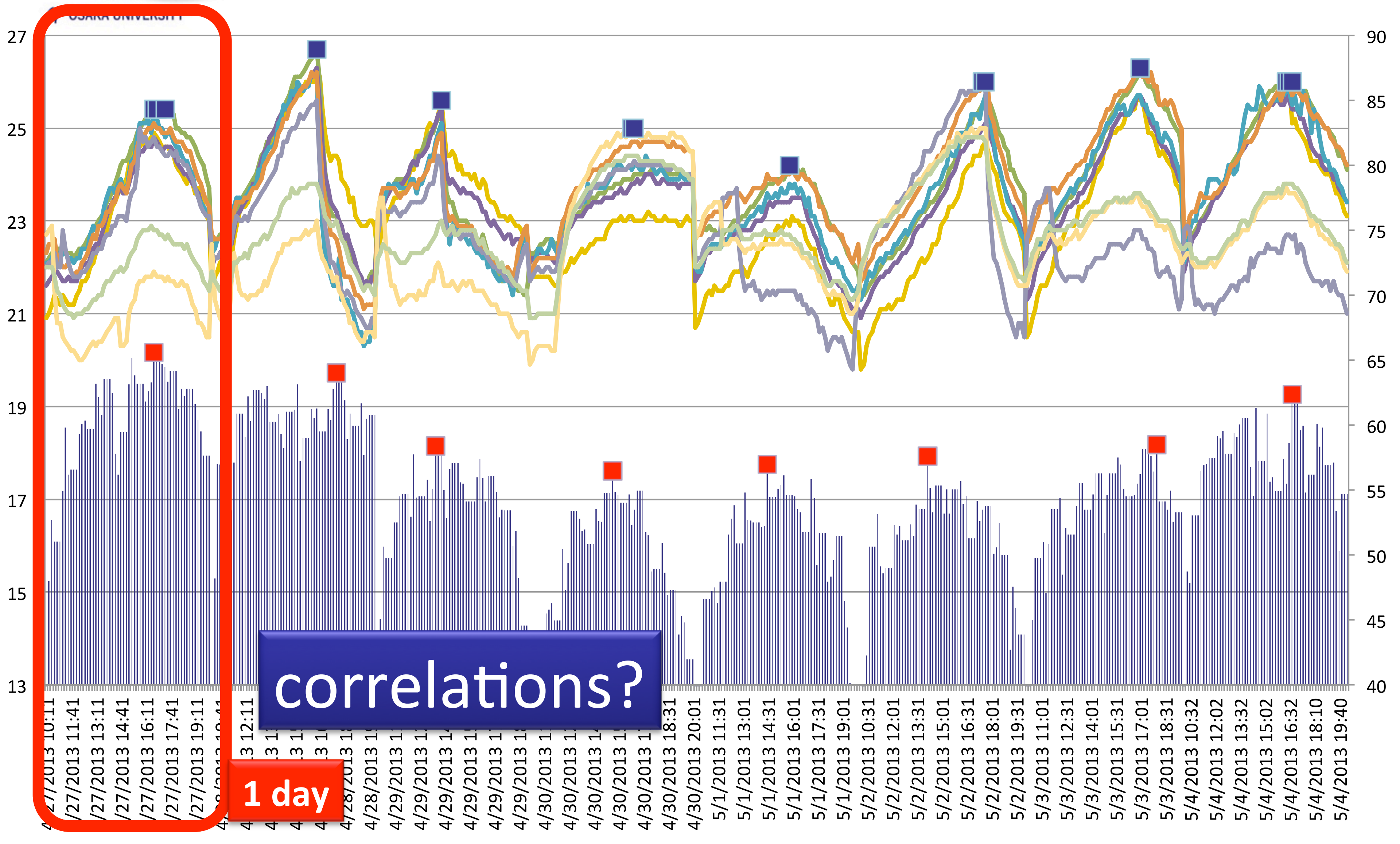


Photo : Grand Front Osaka

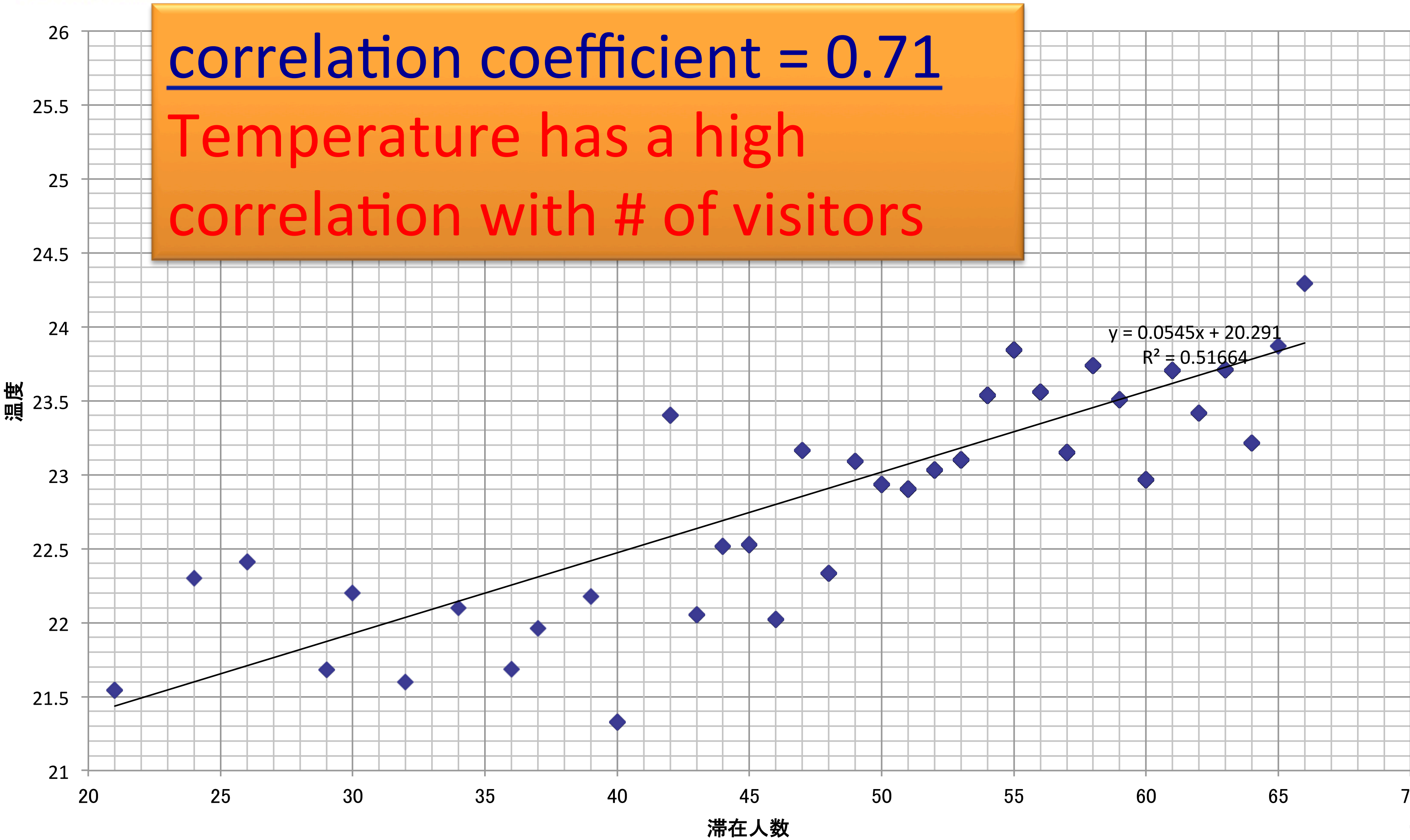
Large Atrium

of visitors vs. temperature
Apr. 27 – May 4, 2013



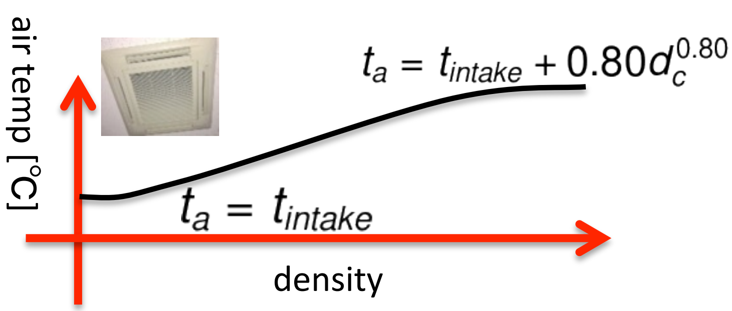
of visitors vs. temperature Apr. 27 – May 4, 2013

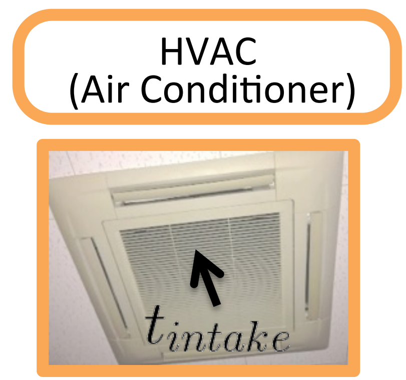
OSAKA UNIVERSITY

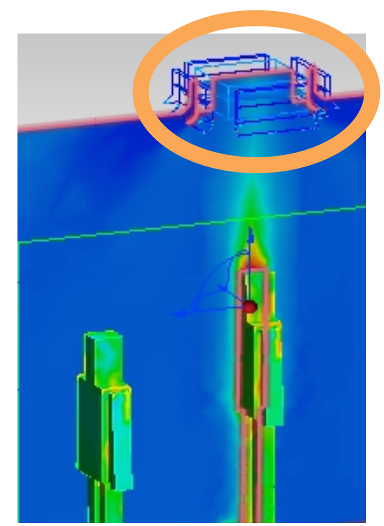


Relation between Intake-air Temperature and Crowd Density

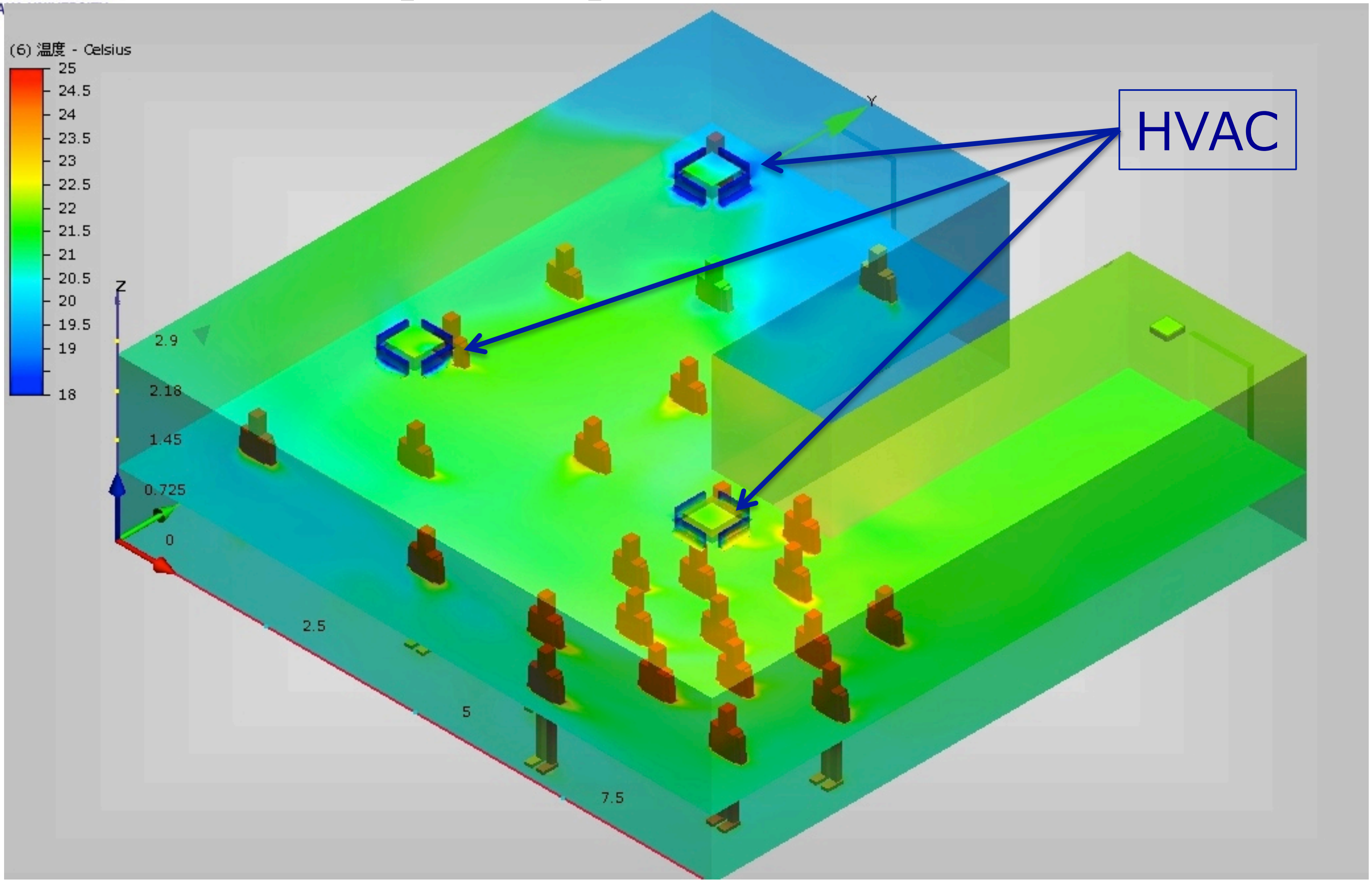
- We assume to use HVAC temp. sensors
  - t_{intake} of HVAC is close to air temperature around human t_a where we do not consider crowd density
- Simulation using Computational Fluid Dynamics
  - $t_a = t_{intake} + 0.80d_c^{0.80}$ with density $\boldsymbol{d_c}$ [person/m^2]







Computational Fluid Dynamics (CFD) Simulation



Our Approach

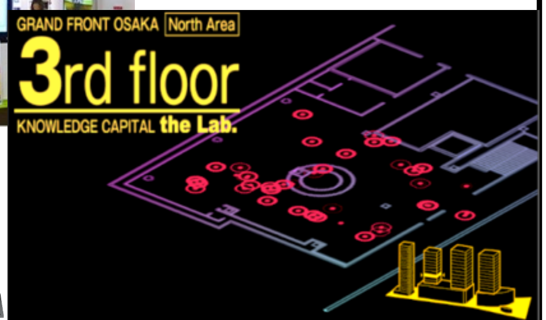
1. Sensing human locations and their density distributions
2. Re-design of thermal comfort index
   – more human-centric
3. Design of feedback effect estimation
   – pinpoint human location, taking the environmental parameters into account
4. Field Experiment

Human-Centric BEMS Concept & Achievement

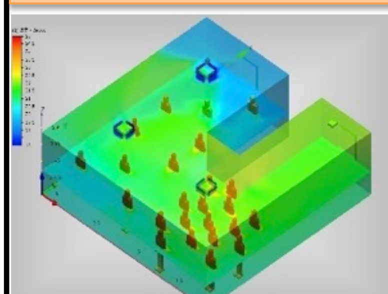
OSAKA UNIVERSITY

1. Human Tracking and Environmental Sensing Technologies

demonstration for 33 months



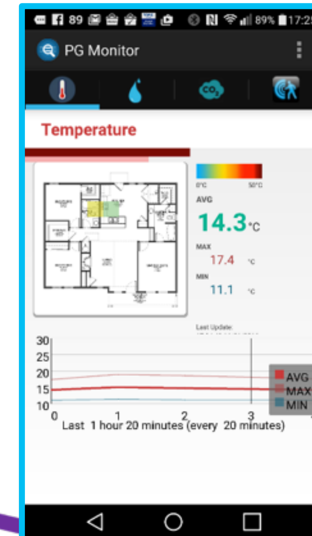
2. Human-Centric BEMS Concept Establishment (New Metrics Design and Feedback Control)

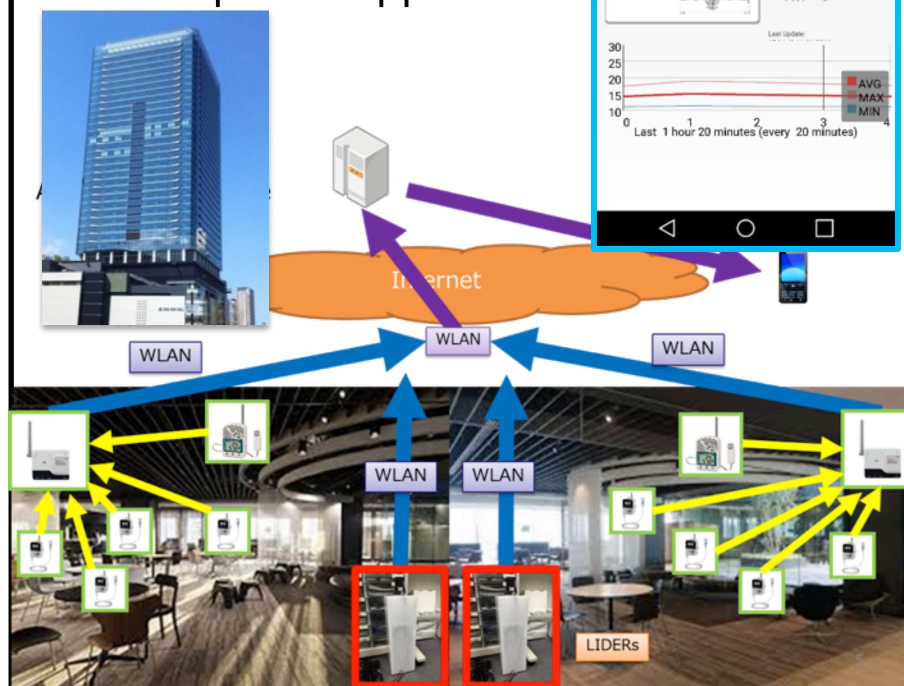


- productivity-based energy efficiency
- human-oriented thermal comfort
- CFD-based feedback function

3. Experiments in Real Environments

- 2 Radars and 52 Temp. Sensors have been set in “Knowledge Salon”
- Cloud Uploading & Smartphone App





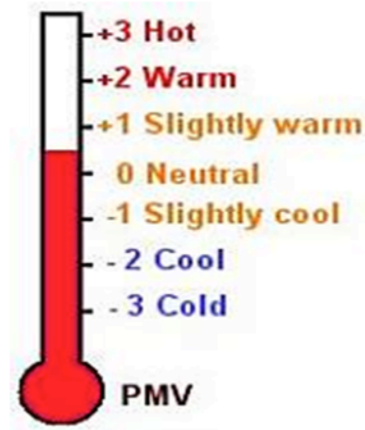
Our Approach

1. Sensing human locations and their density distributions
2. Re-design of thermal comfort index
   – more human-centric
3. Design of feedback effect estimation
   – pinpoint human location, taking the environmental parameters into account
4. Field Experiment

Air Comfort Index

<u>PMV: Predicted Mean Vote</u>

- ISO 7730 (1984)
- explains thermal comfort by human body heat budget
- ranges [-3, +3]
- has many parameters



The PMV Scale

Humans are sources of heat

activity

M: Activity [W/m²]
W: Work Amount [W/m²]

clothes

Icl: Cloth Amount [clo]
Fcl: Extra Cloth Rate [-]

ta: Temperature [℃]

tr: Radiant Temp [℃]
Va: Air Speed [m/s]

pa: steam Pres. [pa]
Va: Convective Rate [W/m²℃]

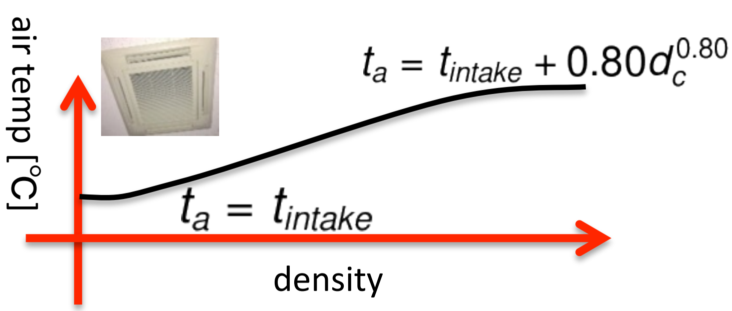
tcl: Cloth Temp. [℃]

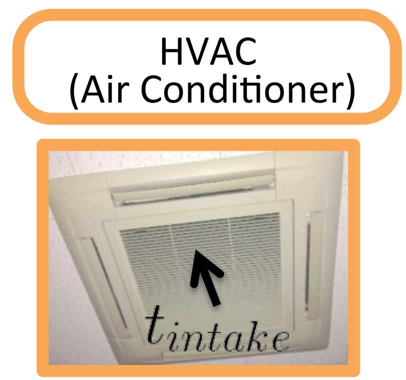
PMV does not consider the influence of neighboring human density

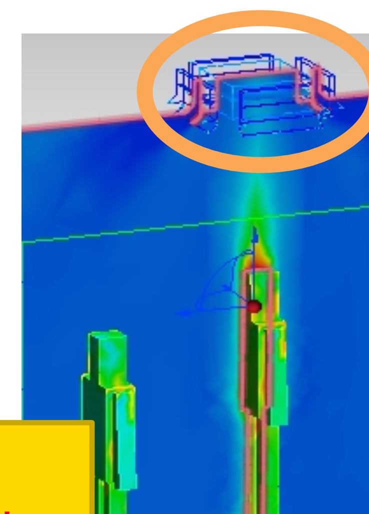
Need Temperature Calibration for Original PMV

OSAKA UNIVERSITY

- We assume to use HVAC temp. sensors
  - t_{intake} of HVAC is close to air temperature around human t_a where we do not consider crowd density
- Simulation using Computational Fluid Dynamics
  - $t_a = t_{intake} + 0.80d_c^{0.80}$ with density $\boldsymbol{d_c}$ [person/m^2]

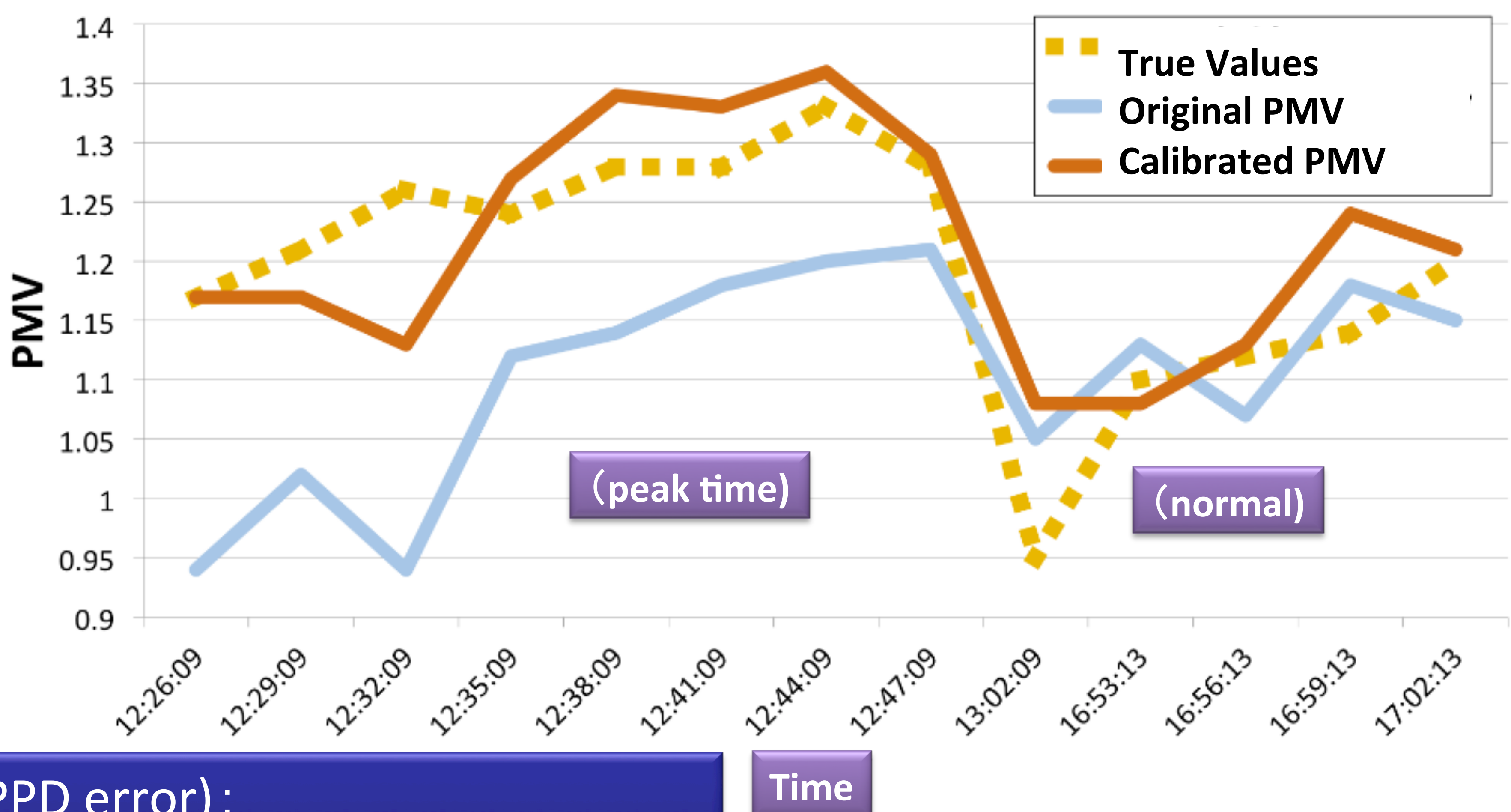






Air Temperature can be estimated by considering both (a) intake-air temperature and (b) crowd density

PMV Estimation Result (in Commercial Complex)

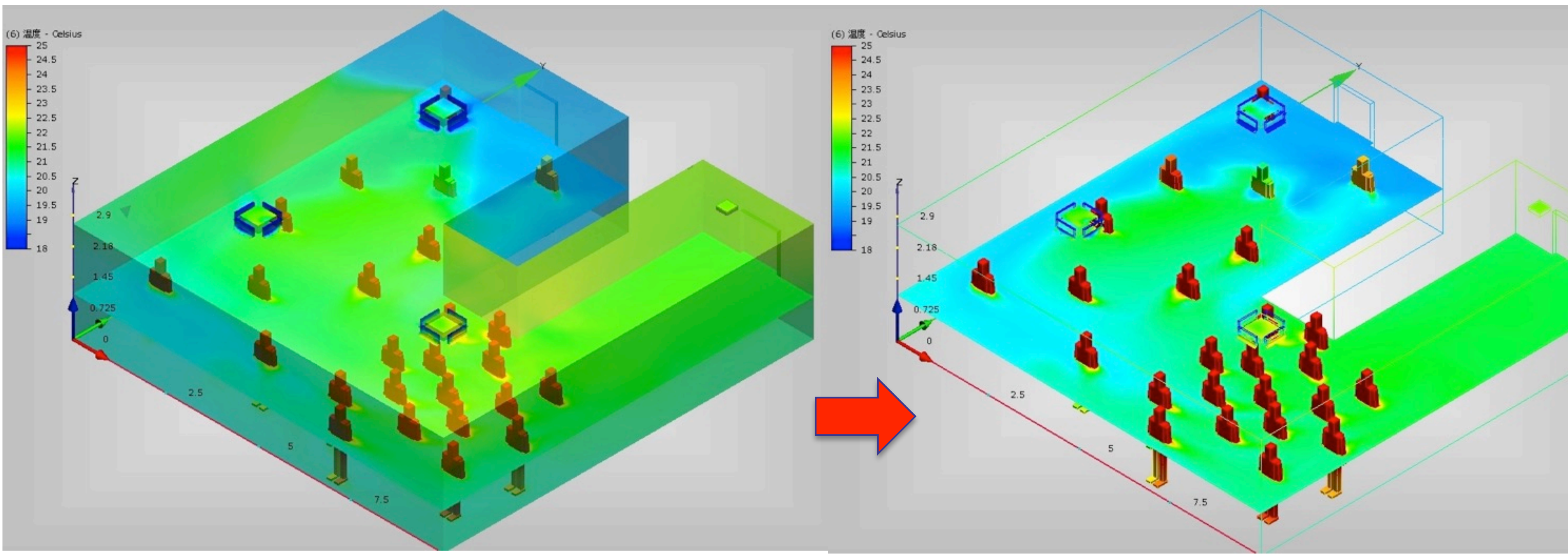


(PPD error) :
15/100 persons -> 5/100 persons

Our Approach

1. Sensing human locations and their density distributions
2. Re-design of thermal comfort index
   – more human-centric
3. **Design of feedback effect estimation**
   – **pinpoint human location, taking the environmental parameters into account**
4. Field Experiment

Computational Fluid Dynamics (CFD) Simulation



- Using the calibrated PMV, we can provide more confortable and effective HVEC controls depending on human density distribution

Our Approach

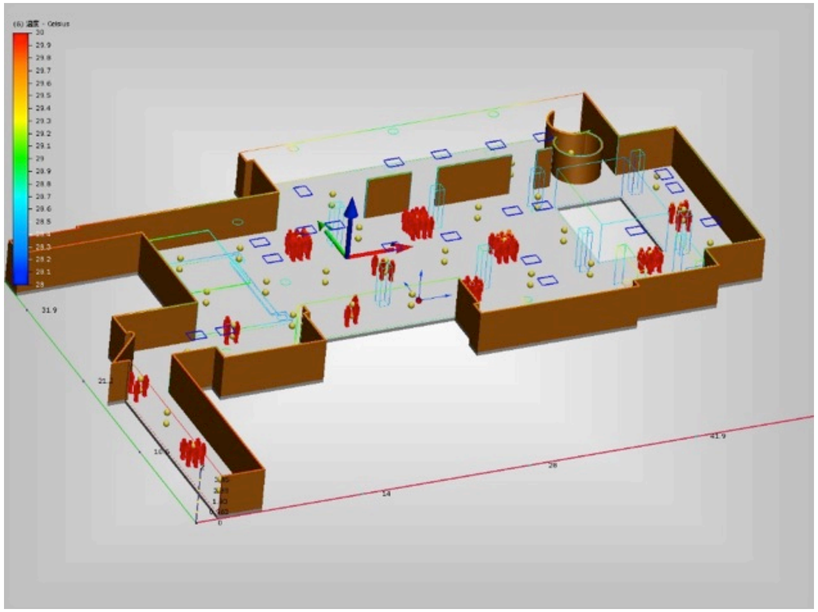
1. Sensing human locations and their density distributions
2. Re-design of thermal comfort index
   - more human-centric
3. Design of feedback effect estimation
   - pinpoint human location, taking the environmental parameters into account
4. **Field Experiment**

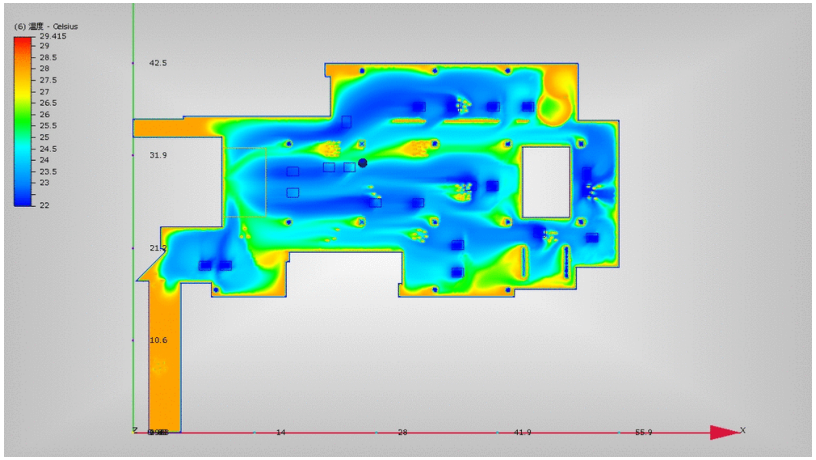
Grand Front Osaka 7F Knowledge Salon

- open 364 days (except new year's day)
- 1400㎡, # of visitors is often over 500

Simulation Settings

- SimulationCFD 2015
- **locations: 80 points**
  - density, distance from nearest HVAC and heights are different
- **Air & HVAC:16 scenarios**
  - T × Tsp: 8 patterns
  - Air Volumes: 2 patterns
- Record temp every min. (till 20 mins.)

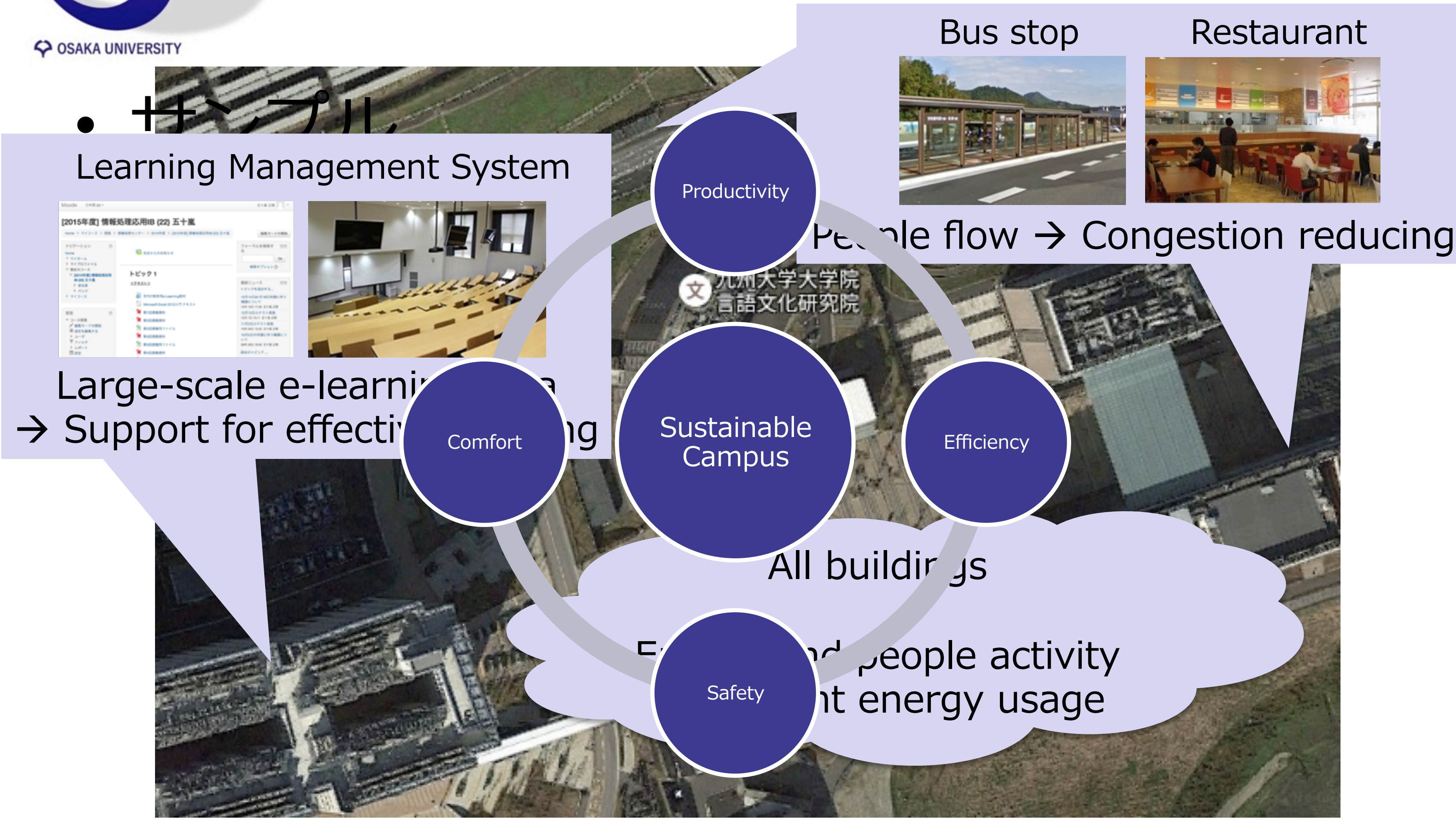




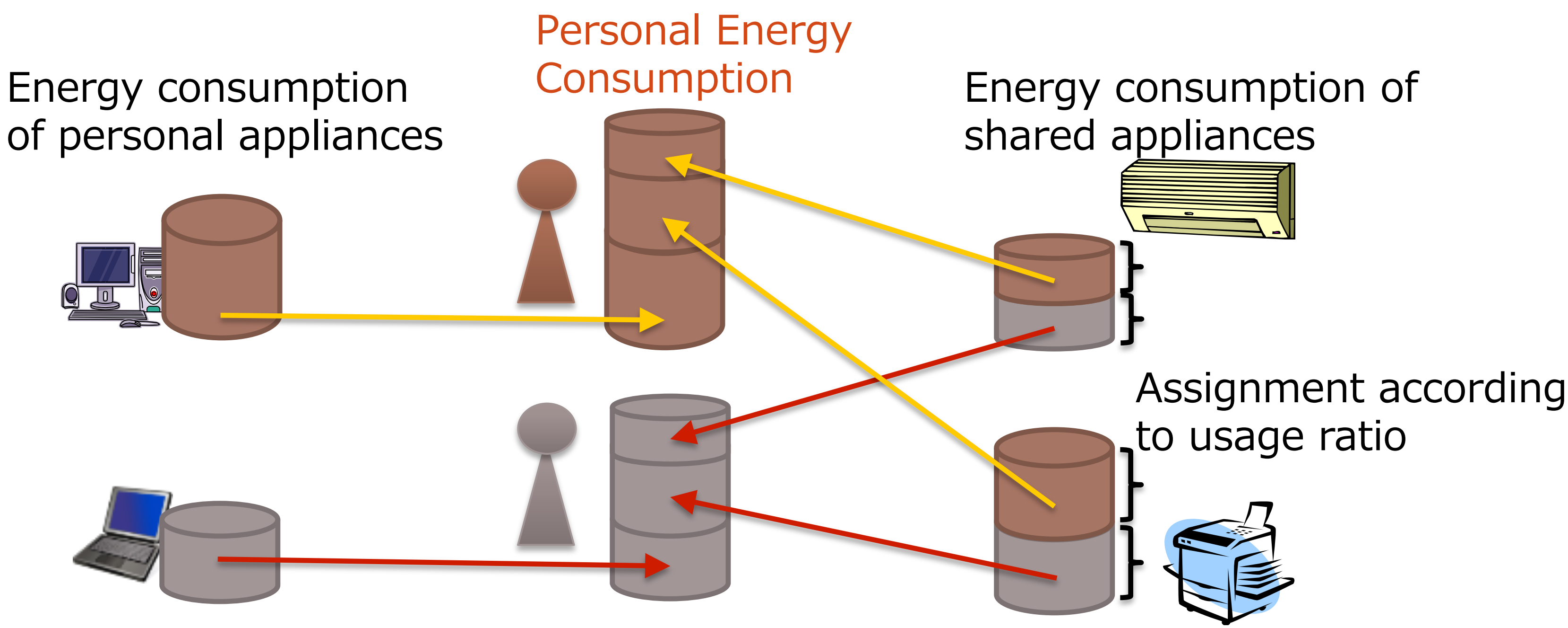
Smart Campus with CPS

Smart Campus with CPS

- サンプル



Our Aim is Personalization of Energy

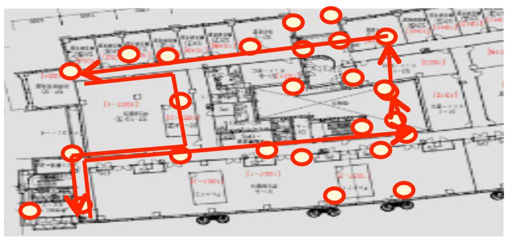


We regard not only personal appliances but also shared appliances as part of personal energy consumption

Purpose
- Smart Campus with CPS -

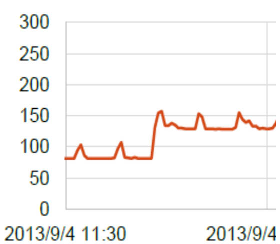
OSAKA UNIVERSITY

Personal behavior obtained from various sensors



Personal trajectory

Energy consumption and environmental information

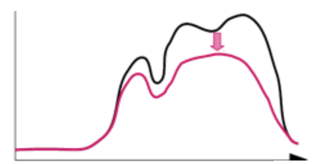


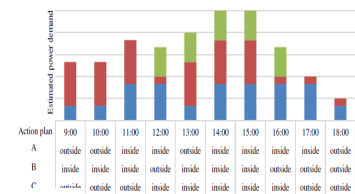
Power Temperature

Efficient energy usage

- Potential estimation of saving energy
- Power demand estimation

Power





Time

- Behavior support

Visualization of sensing data & Indication of behavior support

Saving total amount of energy

Peak cut of energy

Upkeep of comfort

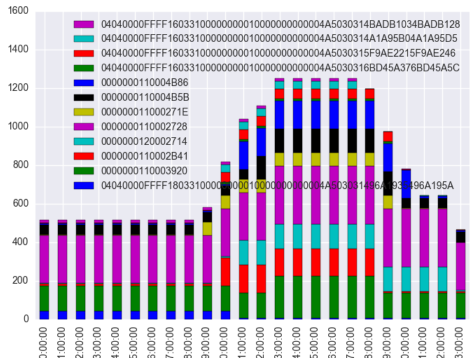
How to "Peak Shift"

Schedule-based recommendation

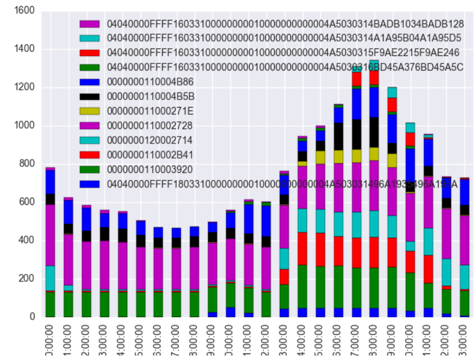
- Asking students to declare their schedule of the next day
  - Arrival time to the laboratory
  - Leaving time from the laboratory
- Power demand estimation based on schedule
  - Estimation algorithm has been developed
- Planning for load balancing with high acceptability
- Recommendation for modification schedule

Experimental Results of Power Demand Estimation

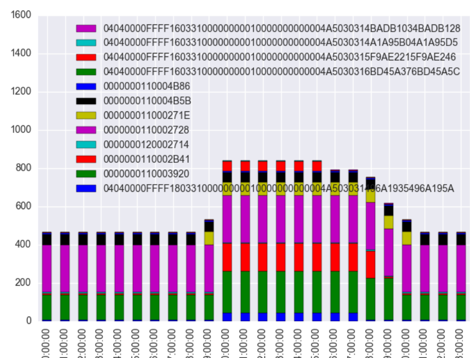
OSAKA UNIVERSITY



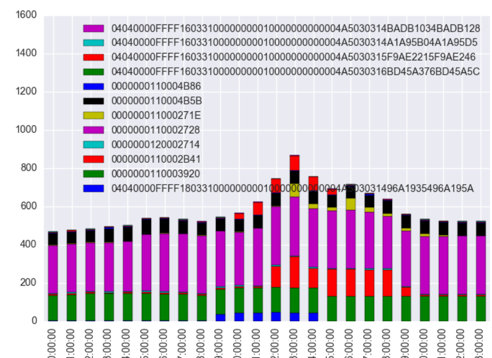
Estimation (Feb. 9)



Ground truth (Feb. 9)



Estimation (Feb. 18)



Ground truth (Feb. 18)

- Peak value is almost accurate
- Peak time is inaccurate
    - Students tend to be late

Beyond the CPS-IIP project:

Future Challenges for Social CPS

OSAKA UNIVERSITY

Need Edge Computing Paradigm

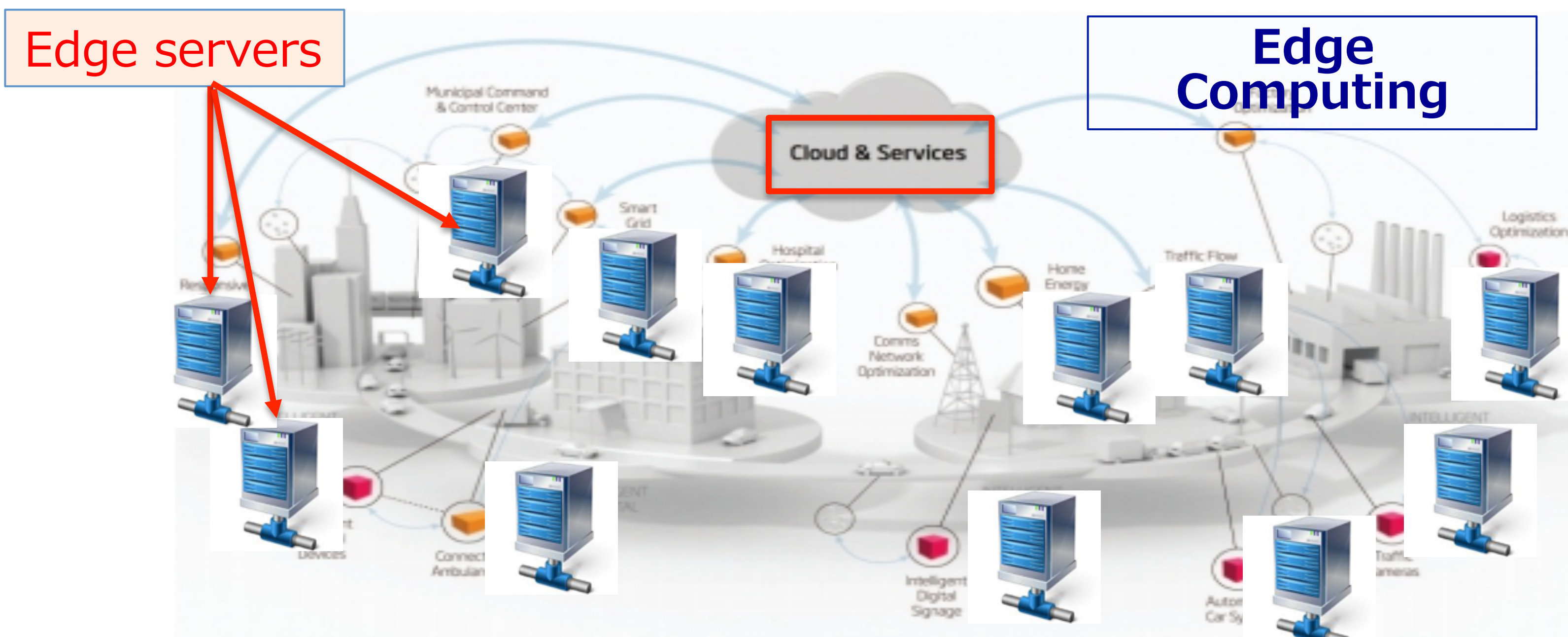
In urban areas, crowd sensing data are continuously welled out everywhere. Soon, such huge data cannot be stored in a cloud server.

(1) Edge servers are installed at target areas' neighborhood

- Several edge servers are located in urban areas.

(2) Autonomous distributed processing at edge servers

- Those edge servers provide local services for target areas collaborated with their neighboring edge servers.



Thank you

higashino@ist.osaka-u.ac.jp