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Data-Driven DSR Control Technology for Energy Sharing

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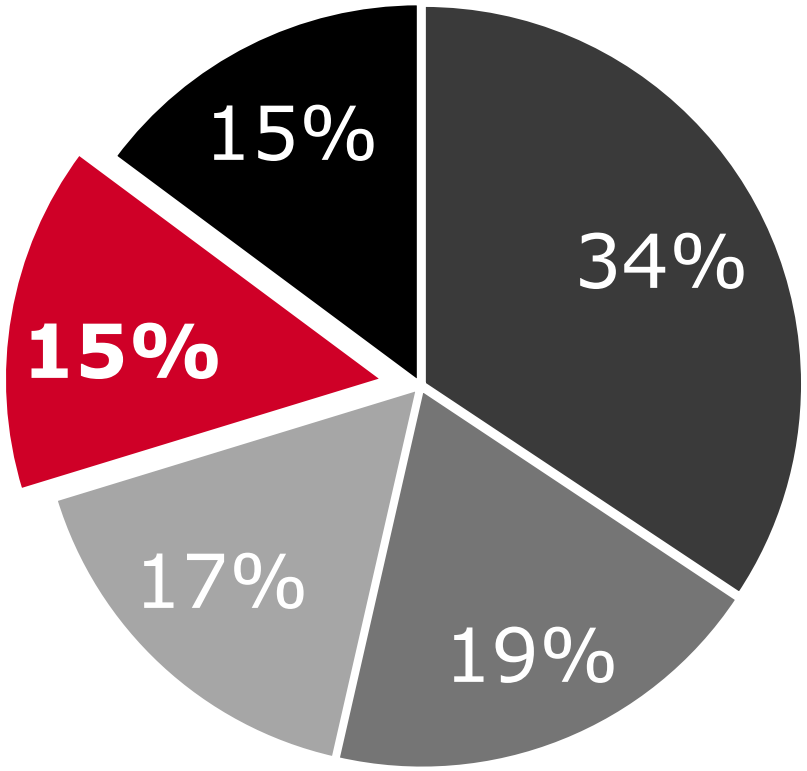
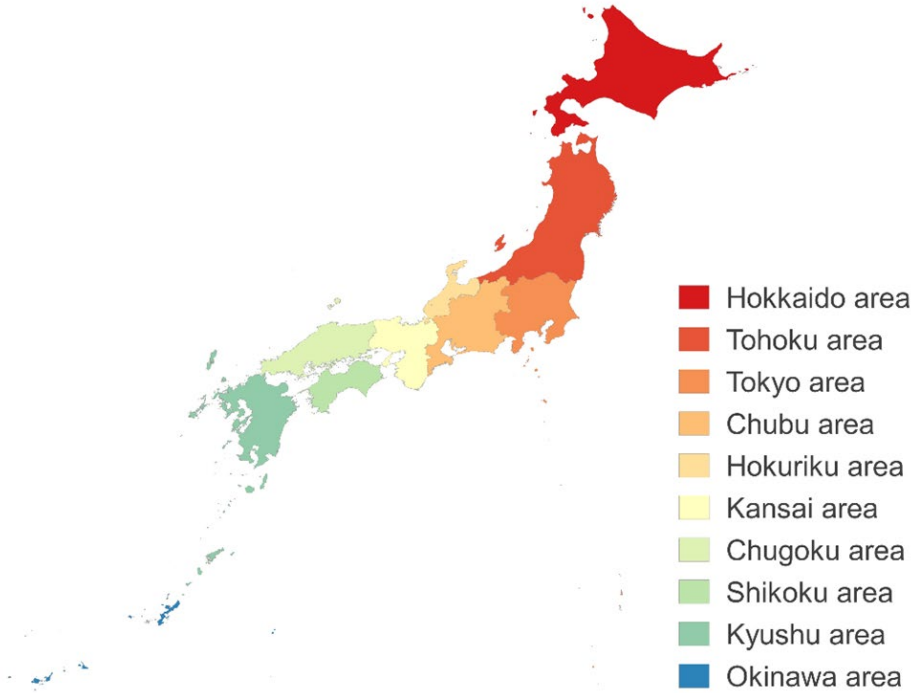
Research background

Decarbonizing the residential sector is challenging because of household heterogeneity



- Industry
- Transport
- Commercial
- **Residential**
- Others

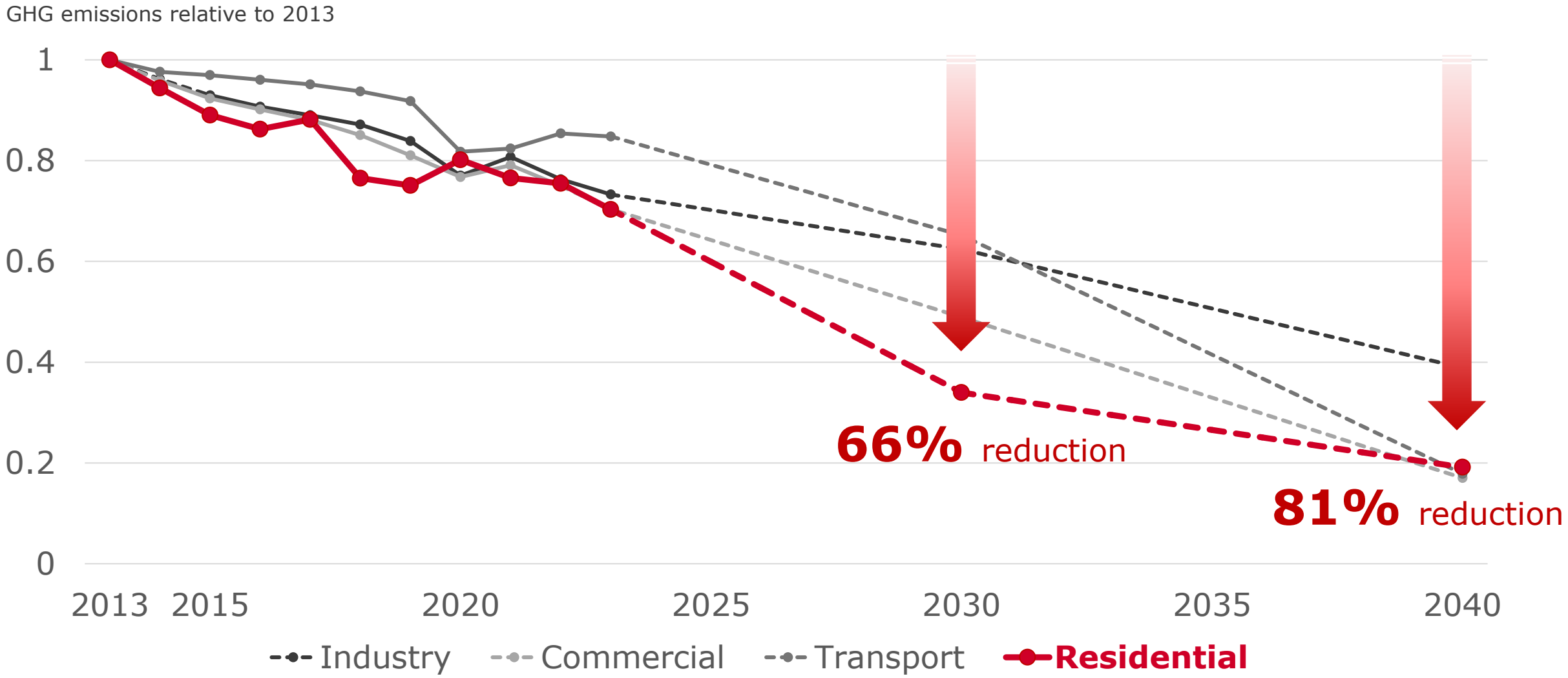
- 56 million households
- Multiple climate zones despite its modest size



"Japan's GHG Emission Data," National Institute for Environmental Studies (2025)

Research background

The residential sector needs to take the lead in decarbonization



"Japan's GHG Emission Data," National Institute for Environmental Studies (2025); "Plan for Global Warming Countermeasures," Ministry of Environment (2025)

Utilization of IoT and Big Data for Decarbonization

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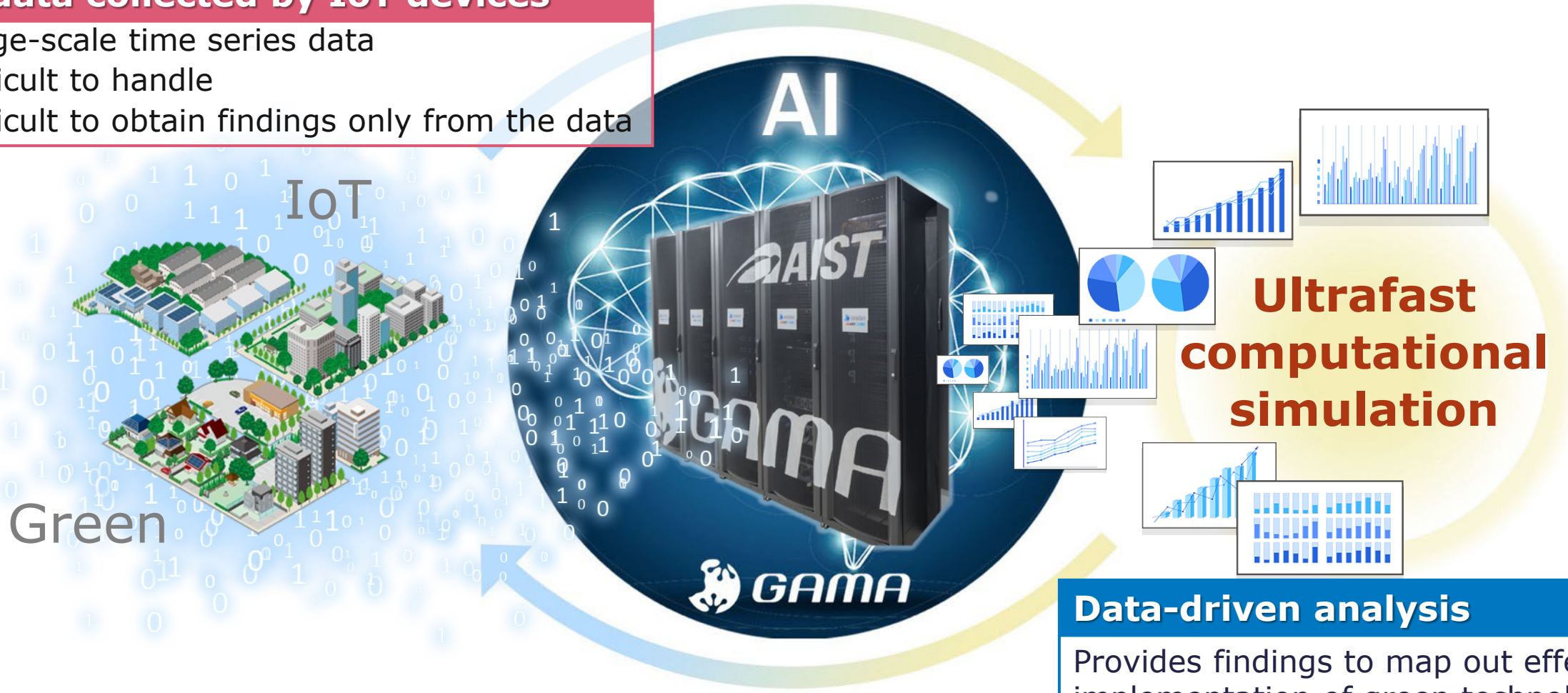
Big data collected by IoT devices

- Large-scale time series data
- Difficult to handle
- Difficult to obtain findings only from the data



Ultrafast computational simulation

Data-driven analysis

Provides findings to map out effective implementation of green technologies

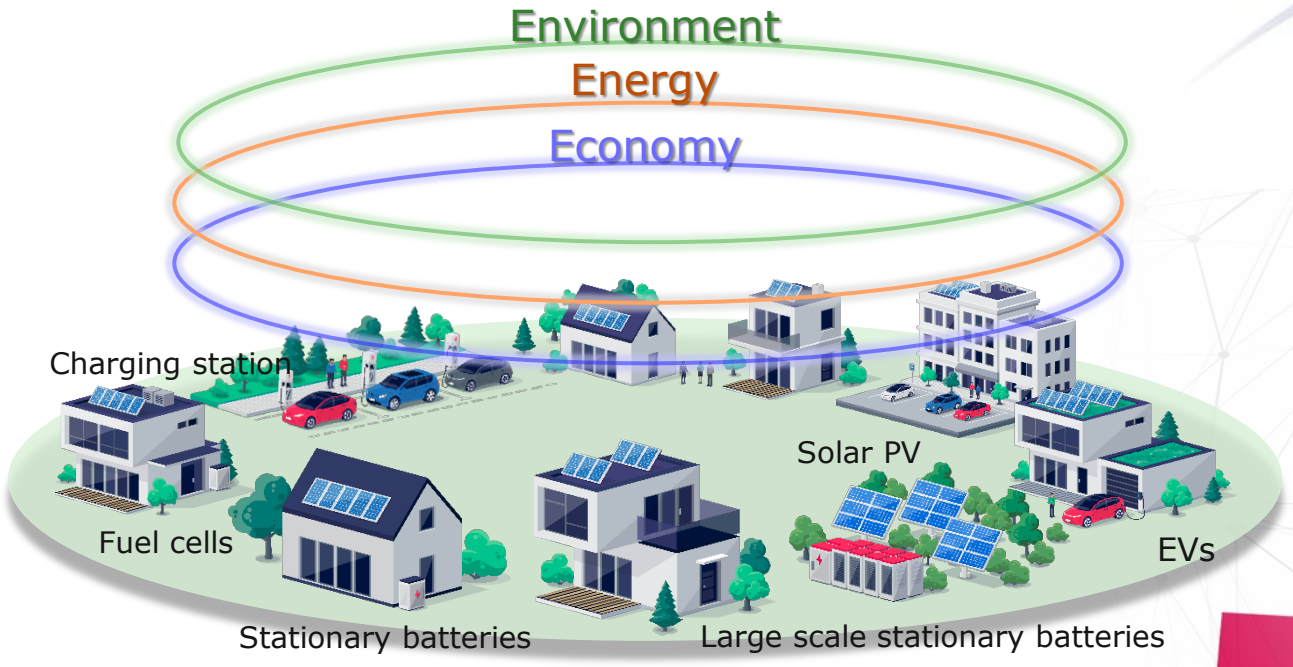
Supercomputer "**GAMA**" (Gigantic Analysis platform using Modelling and AI) :
Tailored for analyzing data collected by IoT devices for a green transition

Our goal

Optimal controls of DSR* across multiple households using big data

*Demand Side Resources (solar PVs, fuel cells, electric vehicles, stationary batteries, ...)

Smart Energy Network



Big data

Deep learning algorithm

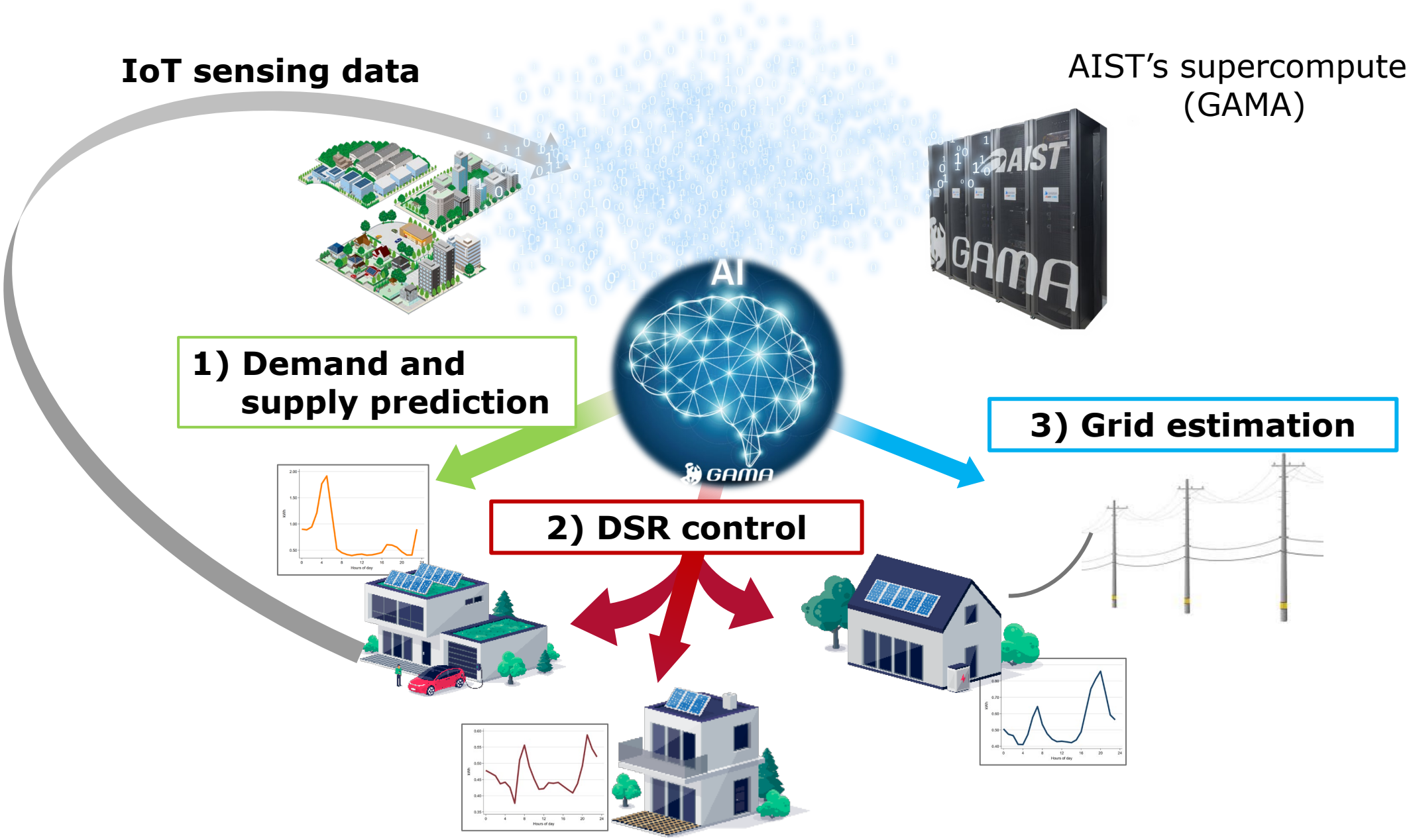
Add new values

- efficient use of energy
- low-carbon energy management
- deployment of renewable energy
- stable electricity supply
- monitoring and crime prevention

DSR controls

Maximize the benefits of variable renewable energy usage

Overview of our research project



International study supported by NEDO

NEDO

R&D Program for Promoting Innovative Clean Energy Technologies Through International Collaboration [JPNP14004]

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- **Extensive experience in big data analysis**
- **Legal constraints limit empirical knowledge for DSR control**

Joint research
Sep 2023--

UC DAVIS

- **Advanced knowledge for DSR control**
- Hourly dynamic pricing is coming
- **Challenges for incorporating household comfort**

Data used in our project

Residential big data in Japan

- **Electricity data from 2011 collected from 140K households**
  - Hourly total consumption
  - Hourly PV generation
  - Operational data on residential battery storage systems of 70K households
  - HEMS data of 10K households
  - Household and house attributes
- **Operational data on 20K HPWH**
- **No data on DSR control**

Thermostat big data in US

- **Thermostat data from 2013 collected from 251K households**
  - 5-minute intervals
  - Thermostat runtime
  - Set temperature
  - Overriding records

https://www.ecobee.com/en-ca/smart-thermostats/smart-wifi-thermostat/

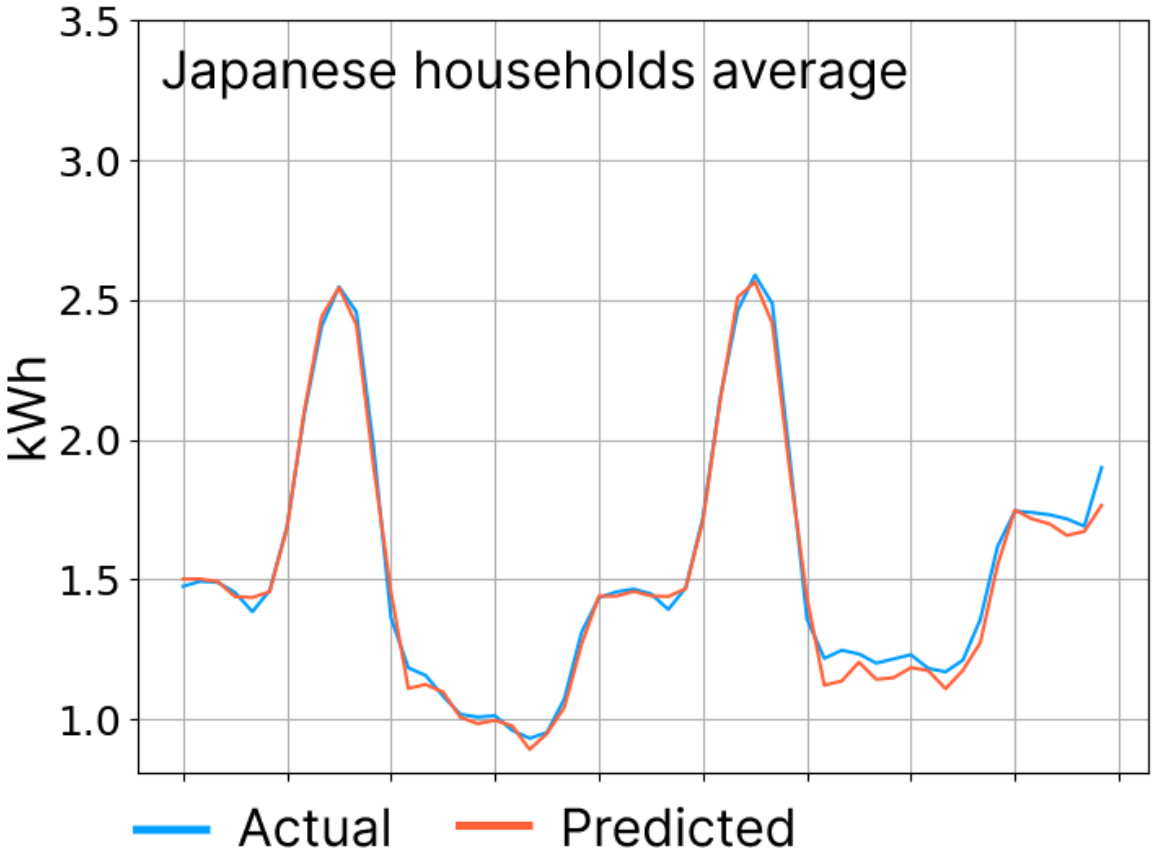
- **Thermostats are controlled daily**
  - Household past thermostat usage
  - Automatic response to price signals of Time-of-Use (TOU) plans

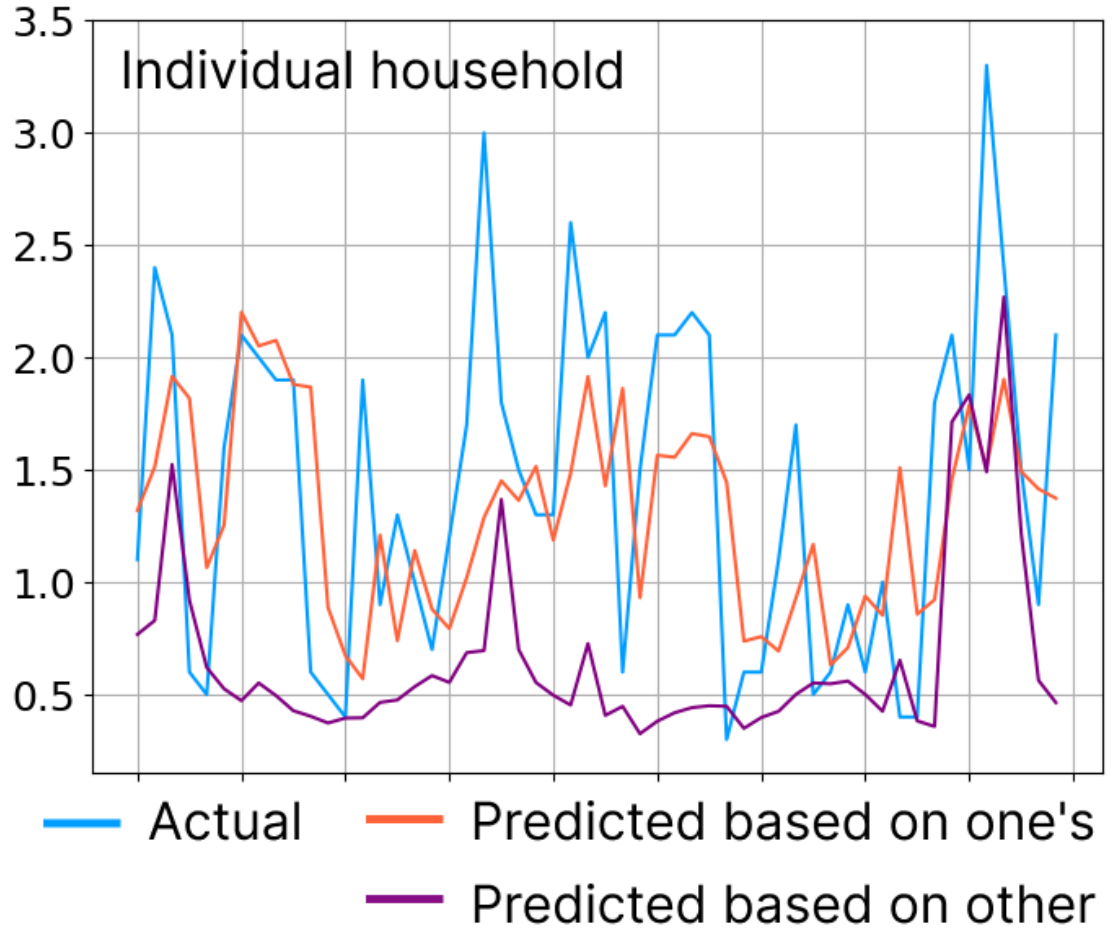
These big data contain vast information in terms of household numbers and diversity, making **AI-driven analysis indispensable**

Demand and supply prediction using Japanese data

Demand and supply prediction

DSR control requires the precise prediction of individual household's energy demand

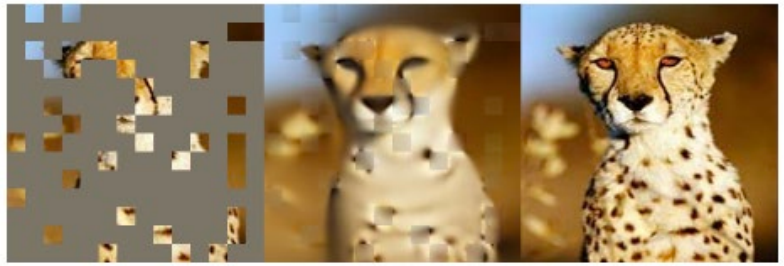


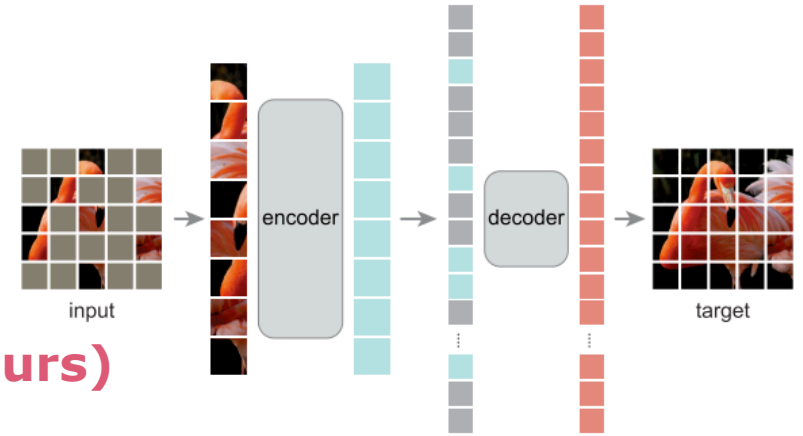


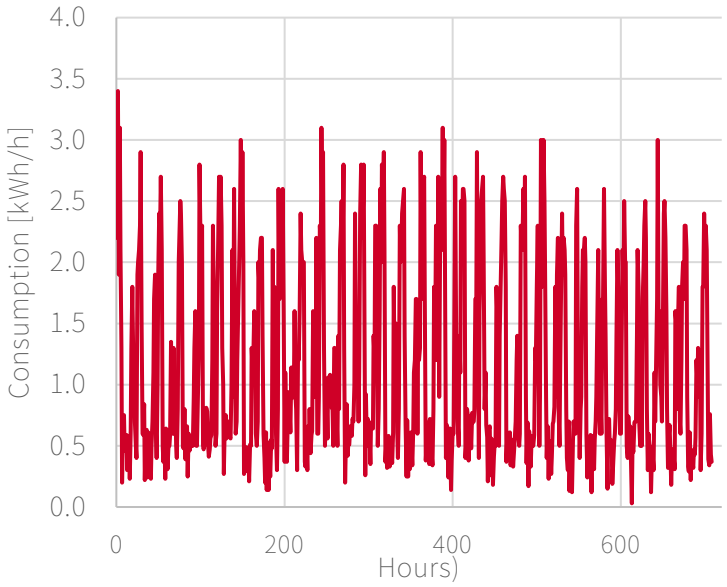
Predictions without aggregation are challenging

Demand and supply prediction

We developed a time-series prediction model by applying **MAE (Masked Auto Encoder)** and its basis (**Transformer**)

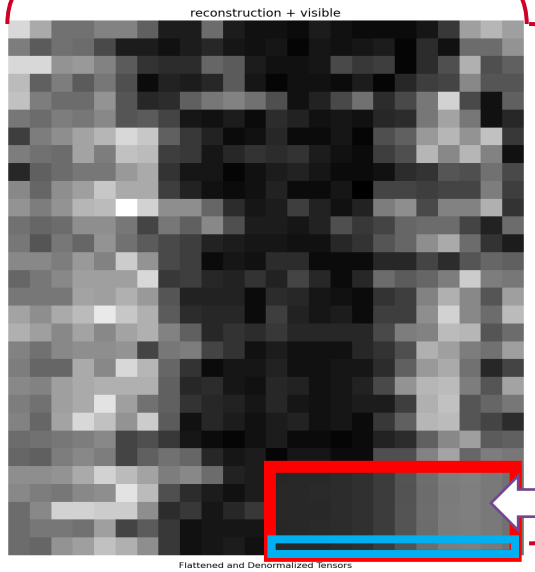






Visualize

24 columns (hours)



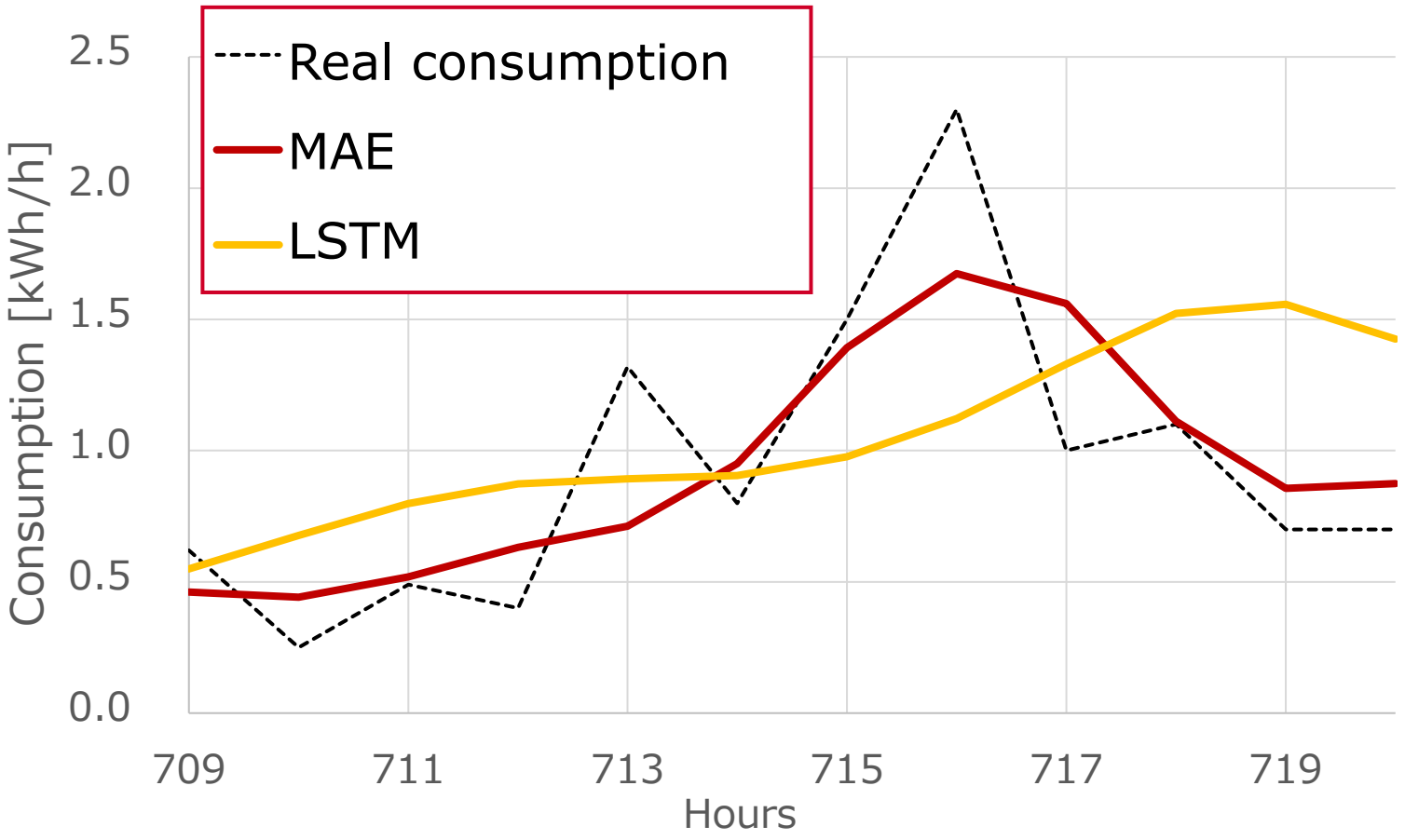
720 pixels in total

30 rows (1 month)

We mask the next 12 hours of electricity consumption and predict them using "image generation"

Demand and supply prediction

12-hour predictions based on MAE and LSTM (Long Short-Term Memory)



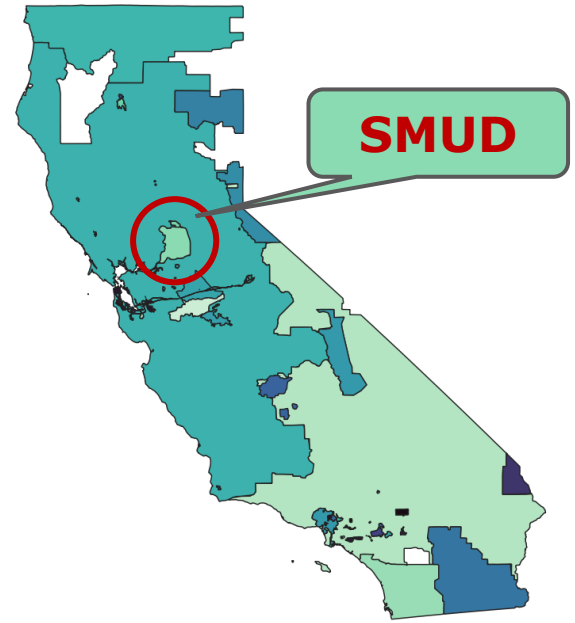
	N	Error	Computation time
MAE	1K	0.1446	0h 57m
	10K	**0.1280**	4h 49m
LSTM	1K	0.1577	8h 56m
	10K	Non-computable	

- MAE can predict individual consumption better than the conventional method (LSTM)
- The computation time is much faster

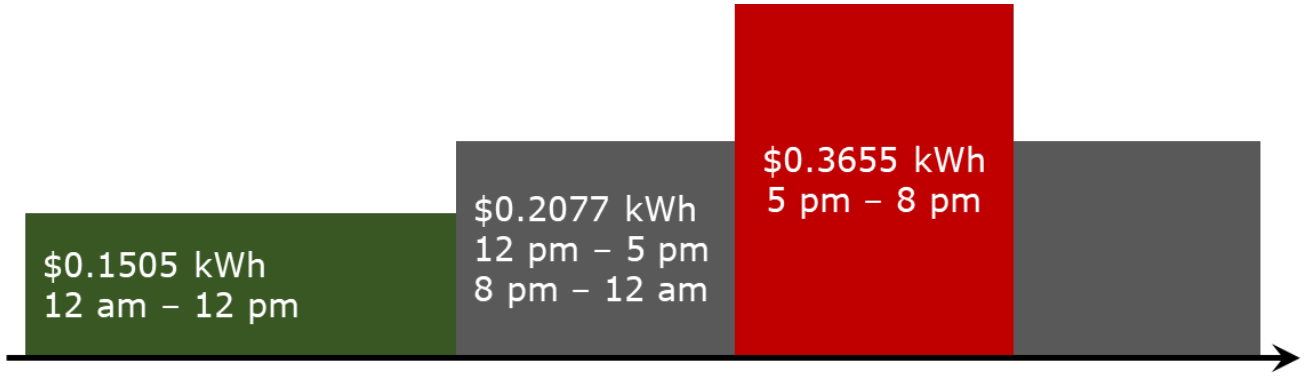
DSR control using Japan and US data

DSR control with US data

- ecobee's smart (Wi-Fi connected) thermostats have automation features
  - HVAC system controls based on occupants' past usage
  - Automated responses to Time-of-Use tariffs
- Data available through the Donate-You-Data program
  - 250K thermostats in the US and 21K thermostats in California
  - Thermostat usage recorded at the 5-minute interval (runtime, setpoint, events,…)
- We study thermostats in Sacramento to study automatic responses to TOU in the SMUD (Sacramento Municipal Utility District) territory

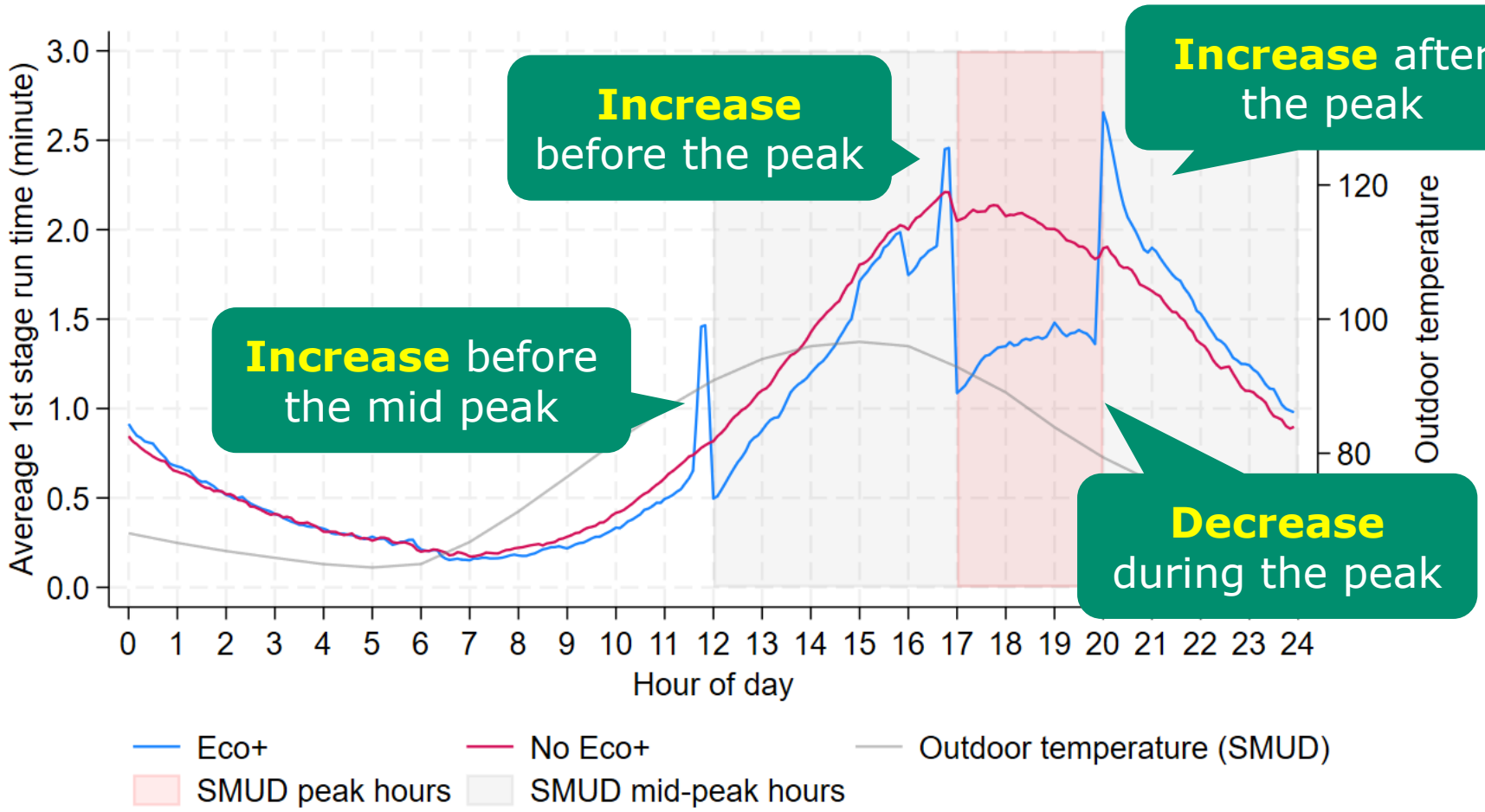


SMUD's TOU in summer
High enrollment rate because of the default switch from the flat rate



DSR control with US data

Average runtime by automated (Eco+) and non-automated (non-Eco+) thermostats



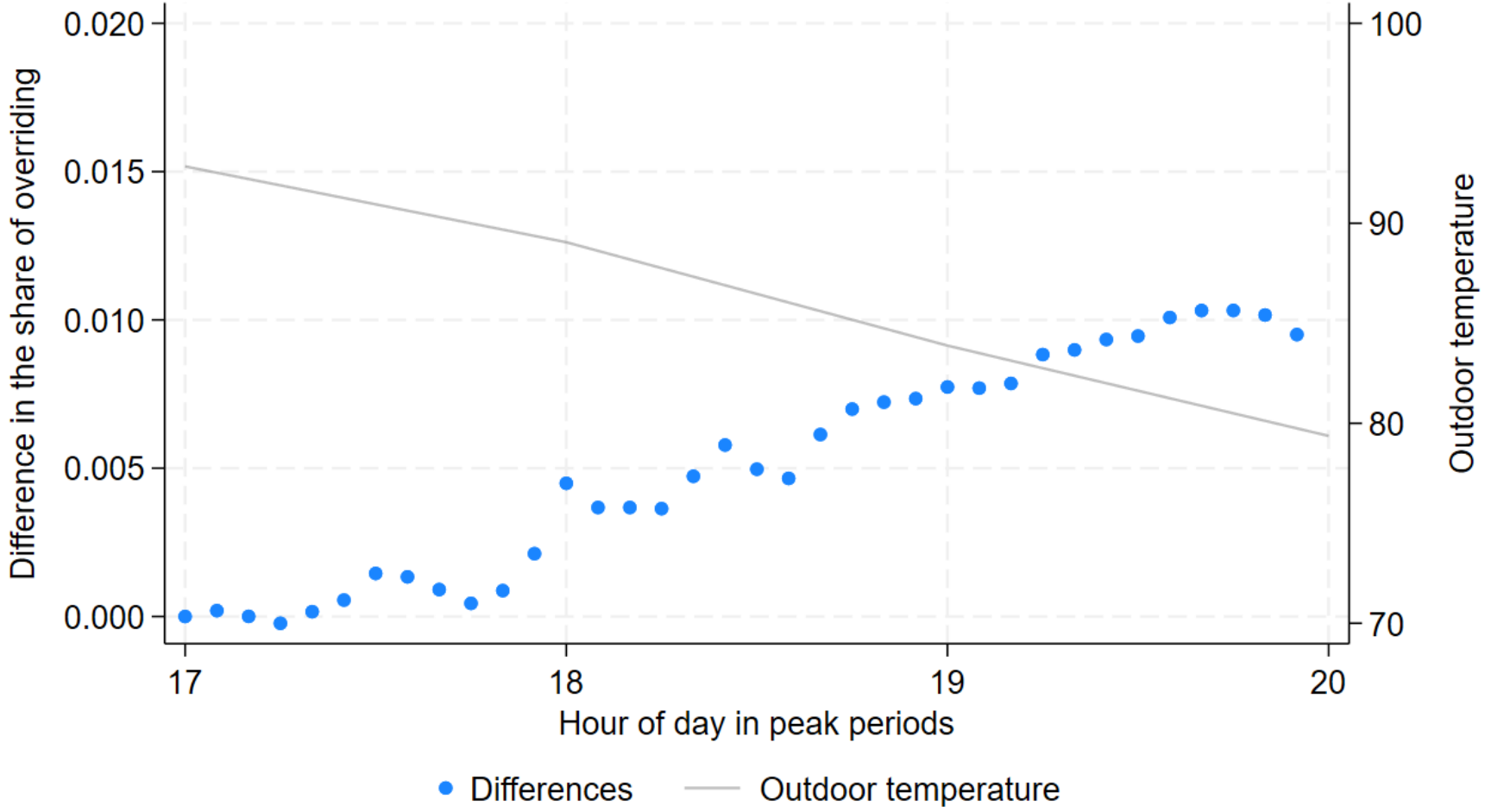
Sample: SMUD thermostats w/ (N=325) and w/o (N=478) Eco+. Period: July 1--Sep 30 (weekdays).

- Automated pre-cooling before the peak
- Set point automatically decreases by 2°F
- In 1 hour after the peak, runtime increases by 8.4 minutes (**+ 0.431 kWh**)

Automated responses to price signals can introduce a capacity problem

DSR control with US data

Difference in overriding over automated and non-automated thermostats

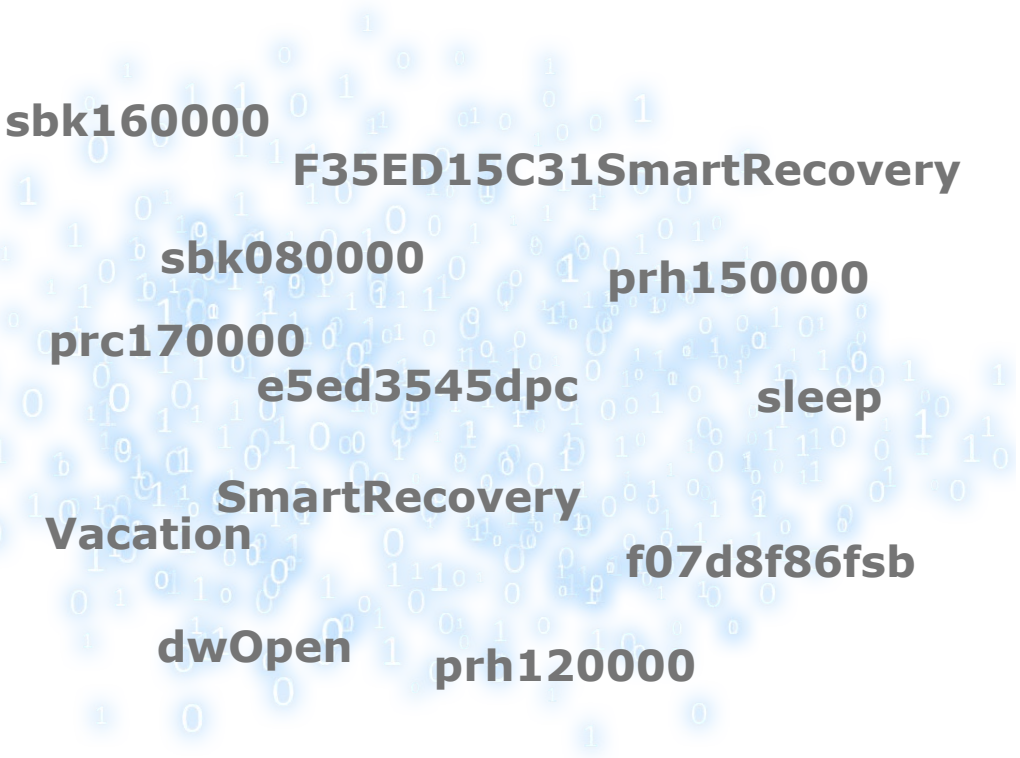


Sample: SMUD thermostats w/ (N=325) and w/o (N=478) Eco+. Period: July 1--Sep 30 (weekdays).

Automated control induces at most 1% increase in overriding (discomfort)

DSR control with US data

AI application to classify user settings



- AUTO/SCHEDULED
- AWAY/UNOCCUPIED
- HOME/OCCUPIED
- MANUAL/HOLD
- PRE_COOLING (TOU AUTO)
- SETBACK (TOU AUTO)
- SLEEP/NIGHT
- UNCLASSIFIED

More than 1,000 user settings can be categorized into less than 10 classes

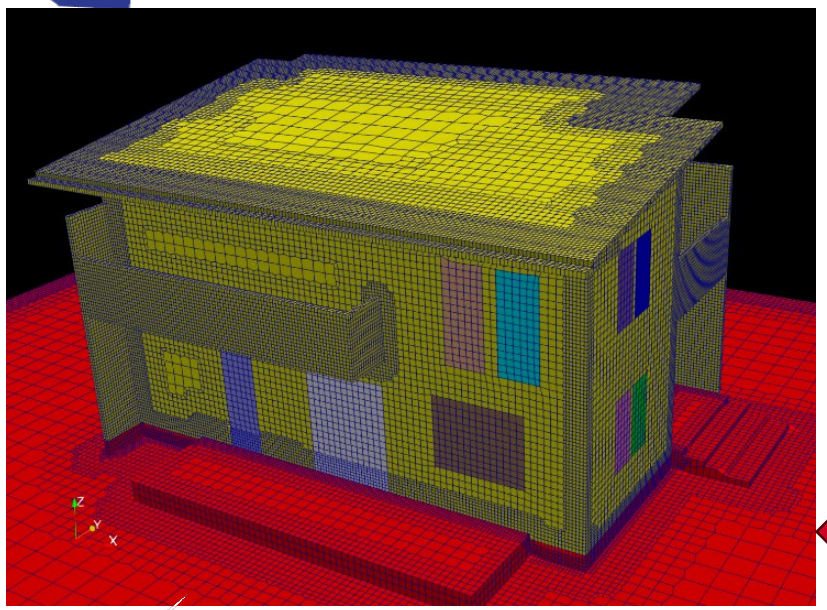
Digital twin technology for DSR controls with Japanese data

Digitization

Physical house

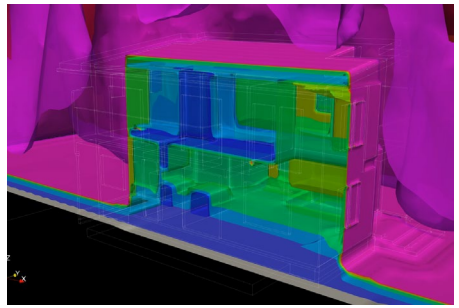
150 sensors inside

Digital house



DSR control

- HVAC systems
- Battery storage
- V2H systems
- HPWH



Feedback

Implications for physical houses

Data-driven evaluation of social acceptance

Data driven evaluation of social acceptance

- For the diffusion of data-driven DSR controls, we need what consists of their social acceptance
- Data-driven evaluation is infeasible due to the lack of markets for DSR controls

We created a market of DSR controls to evaluate their social acceptance

Conjoint analysis from a choice experiment

- Create hypothetical services to study consumer preferences
- Characterize services by **attributes** and generate multiple hypothetical services by changing attribute **levels**
- Evaluate the impact of attributes on willingness to purchase

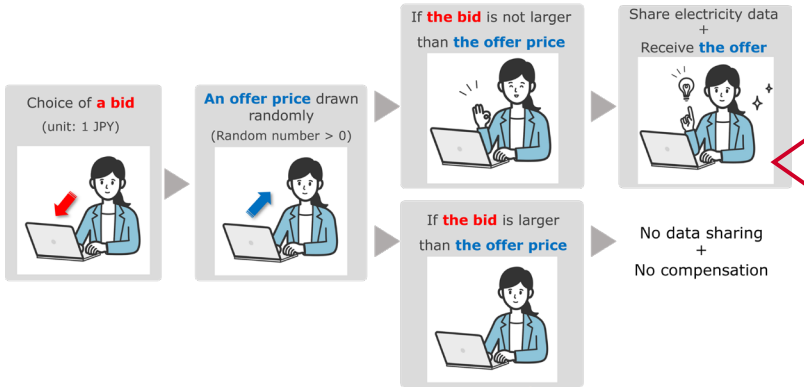
Hypothetical plans from five attributes and their levels

Consumers choose the best and worst plans

	Plan 1	Plan 2	Plan 3	Plan 4	Plan 5 (Status quo)
Annual energy savings rate	5%	10%	20%	20%	0%
Target equipment	Air conditioner	Air conditioner	Water heater	Storage system	
Override option	No override	Override except 6-10am	Override at any time	No override	
Information that users provide	Postal number	Postal number Household Electricity use	Postal number Household Electricity use Lifestyle	Postal number Household	
Fee (JPY per year)	¥5,000	¥20,000	¥5,000	¥20,000	¥0

Economic experiment with the BDM mechanims

- Incentives for consumers may be necessary to encourage data provision for data-driven DSR control
- Conduct an economic experiment to create a trading market for electricity data and evaluate its value



BDM mechanism

Submit a bid

▼

A computer decides an offer price randomly

▼

The transaction is determined based on the bid and offer price

Data driven evaluation of social acceptance

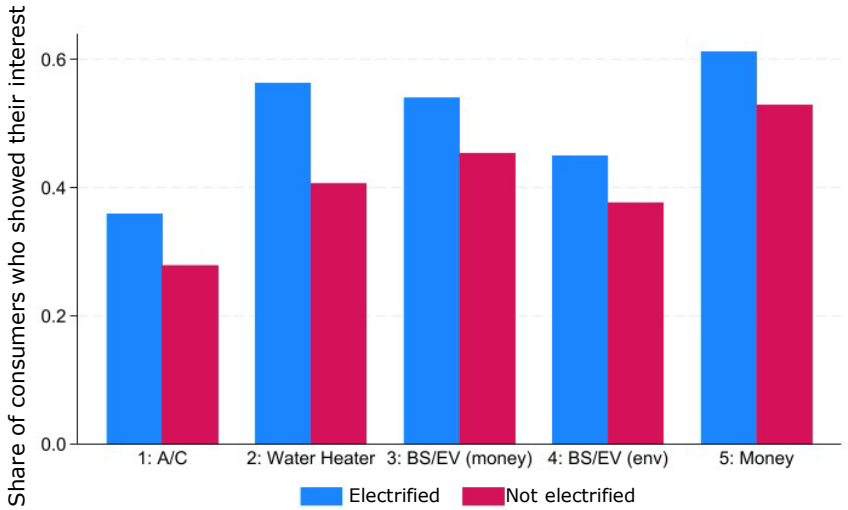
Conjoint analysis from a choice experiment

Methods

- Web survey implemented in June 2024
- 2,900 consumers aged above 19 in Japan (50.2% electrified)

Results

- Consumers prefer lower service fees
- Being able to override controls anytime is strongly preferred
- Preferences over DSR: **HPWH>HVAC>Battery storage>EV**



Economic experiment with the BDM mechanims

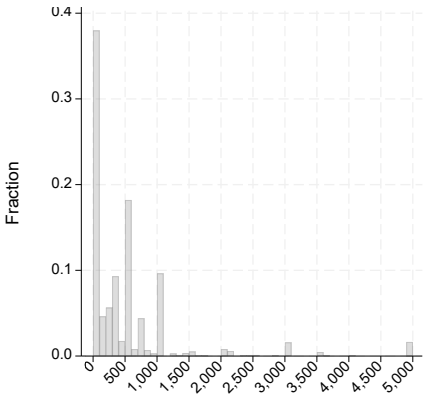
Methods

- Web experiment implemented from Dec 2024 to Feb 2025
- 20,951 consumers aged above 19 in Tokyo and Chubu

Results

Q. Can you share your electricity data with AIST?	Share
Yes, for free	**12%**
Yes, if compensated	**46%**
Never	**43%**

- **60% agreed with data sharing**
- 75% demand less than 500 JPY/month for data sharing
- DSR must yield more than 500 JPY/month benefits



Concluding remarks

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- We analyze energy big data combining AI, data science, and environmental and energy economics
- The data-driven approach helps us incorporate household comfort into DSR controls and can enhance social acceptance
- International collaboration on joint data analysis is very welcome!

This study was supported by “Research and Development Program for Promoting Innovative Energy and Environmental Technologies Through International Collaboration (JPNP14004)” of the New Energy and Industrial Technology Development Organization (NEDO), Japan.