

# Assessing climate sensitivity of hourly electricity demand in Japan

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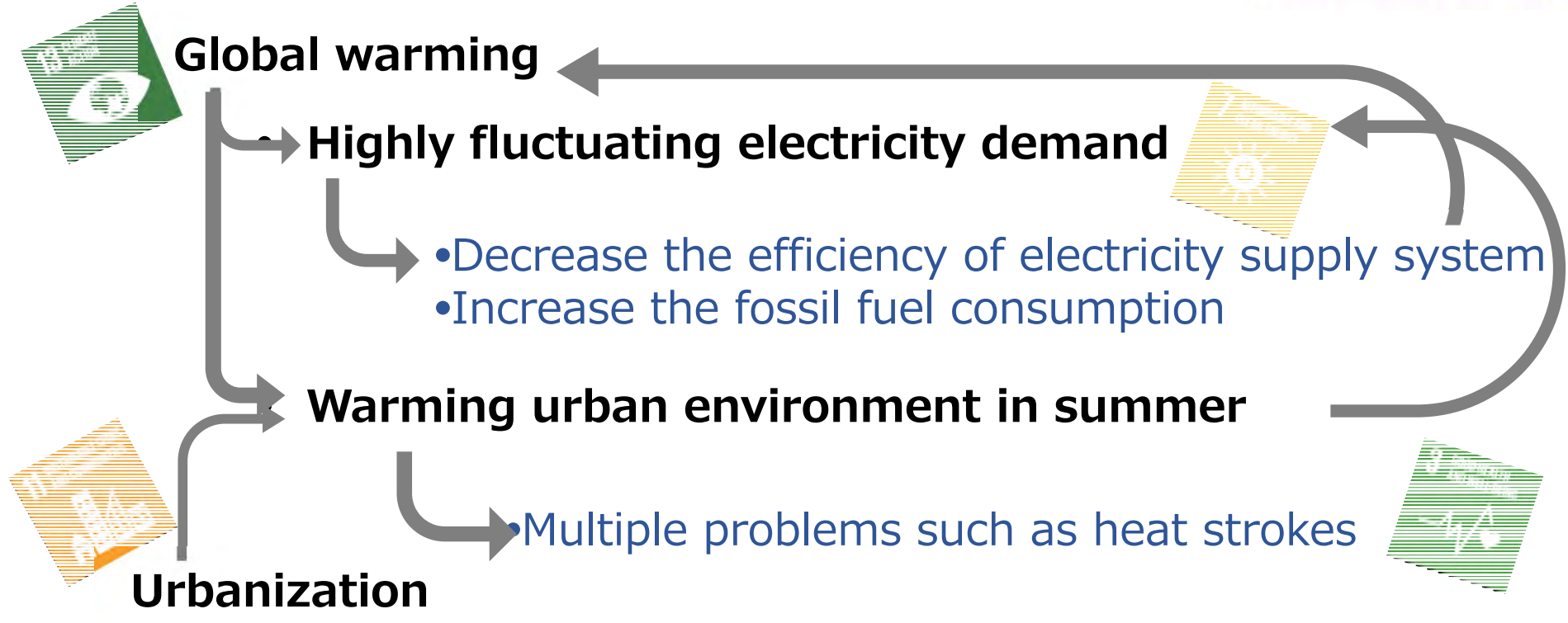
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# ■ Motivations



It is important to clarify the relationship between **weather conditions** and the **hourly electricity demand**

# Overview

## Target Areas

- Jurisdiction of 10 electric power companies in Japan (EPC)



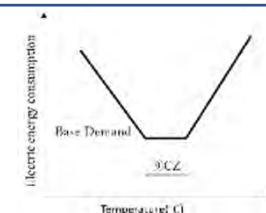
## Method over view

### Build regression models for each EPC



### Simulation

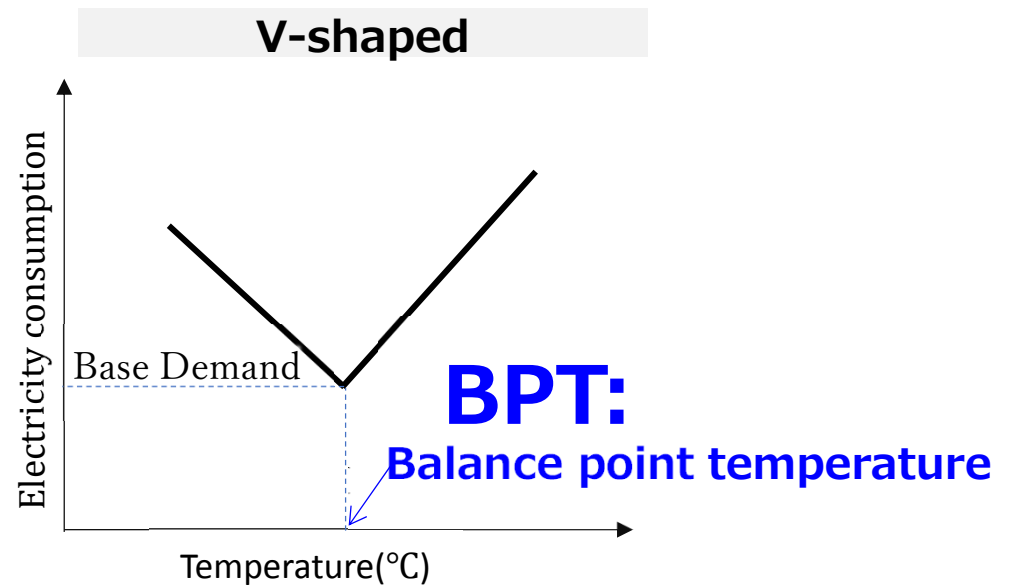
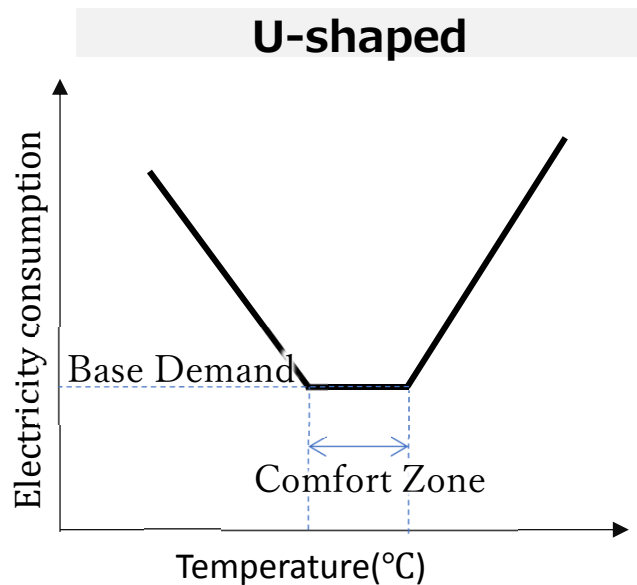
Represent the **Temperature response functions**  
Based on simulation by the constructed models



Understanding the relationship  
between **weather conditions** and the **hourly electricity demand**

# Temperature response function (TRFs)

\*Also called Energy signature



Application:

**TRFs** → **Basic Units**

- **BPT** → Reference temperature for HDD/CDD
- **BPT**, Slope → Electricity demand projection

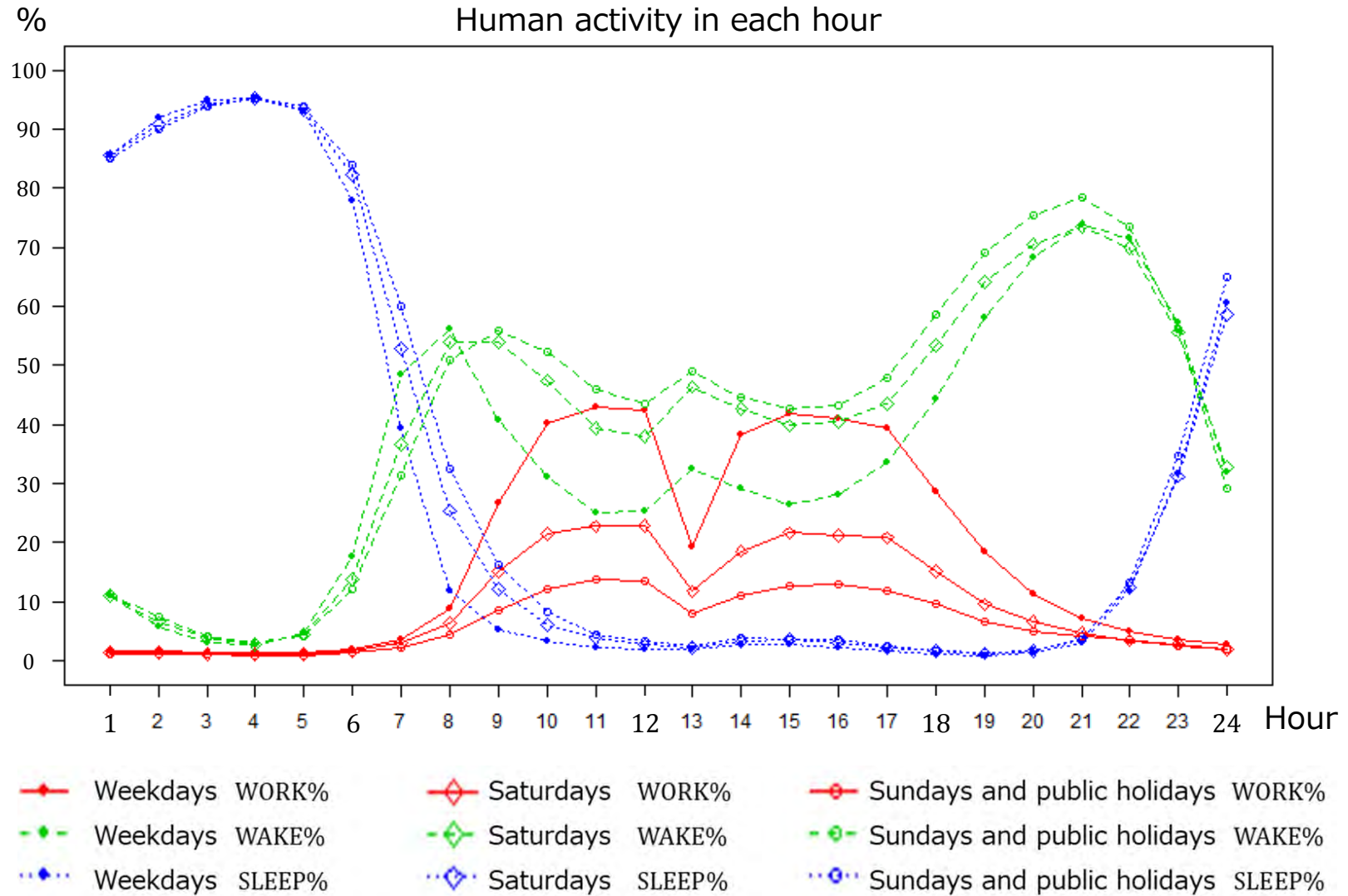
**Important!**

Affects  
assumptions of  
other models!

# ■ Data and Variables

	Names (Abbreviations)	Units	Data Description	Data Source	
Explained Variable	<b>Historical electricity demand (EC)</b>	MWh	Hourly electricity demand in each EPC jurisdictional area.	Organization for Cross-regional Coordination of Transmission Operators Japan,	
Predictors	Historical weather	<b>Temperature (TEMP)</b>	°C	Hourly averaged air temperature in FY2016 and FY2017	Japan Meteorological Agency
		<b>Humidity (HUM)</b>	%	Hourly averaged relative humidity in FY2016 and FY2017	
		<b>Solar radiation (SUN)</b>	MJ/m <sup>2</sup>	Hourly averaged total radiation in FY2016 and FY2017	
		<b>Wind speed (WIND)</b>	m/s	Average wind speed in ten minutes before each hour in FY2016 and FY2017	
		<b>Rainfall amount (RAIN)</b>	mm	Hourly total rainfall amount in FY2016 and FY2017	
		<b>Snow depth (SNOW)</b>	cm	Hourly total snow depth in FY2016 and FY2017	
	Thermal index	<b>Discomfort Index (DI)</b>	–	Discomfort Index. $DI = 0.81 (TEMP) + 0.01 (HUM) (0.99 (TEMP) - 14.3) + 46.3$	Derived from Historical Weather Data Above
		<b>Wind Chill (WCI)</b>	–	Wind Chill Index. $WCI = (33 - TEMP)(10.45 + 10(WIND^{0.5}) - WIND)$	
	Human activity	<b>Holidays and weekends dummy (HDD)</b>	–	Weekends, holidays, the New Year, and the Obon Festival were set as 1, and all other days were set as 0 in FY2016 and FY2017	Calendars in FY2016 and FY2017
		<b>Working people (WORK%)</b>	%	The percentage of people who are working at the hour.	NHK Broadcasting Culture Research Institute.
		<b>Awake people (WAKE%)</b>	%	The percentage of people awake in their homes at the hour.	
		<b>Sleeping people (SLEEP%)</b>	%	The percentage of people who are sleeping at the hour.	

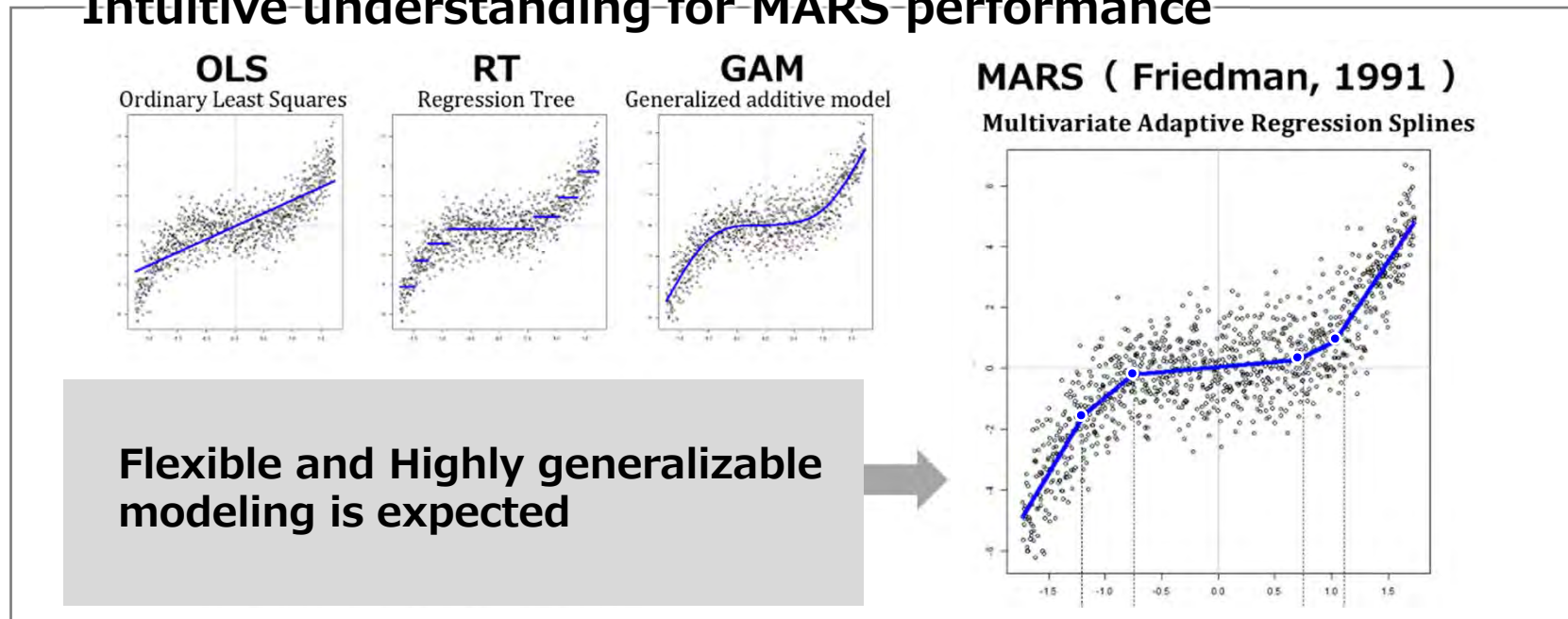
# Human activity data



## MARS : multivariate adaptive regression splines (Friedman, 1991)

- **Captures** the complexity of the potential model by applying a locally linear models.
- **Selects** important variables during the model building process.
- **Showed** excellent prediction performance in short-term power consumption modeling (Sigauke & Chikobvu, 2010; Al-Musaylh, Deo, Adamowski, & Li, 2018)

### Intuitive understanding for MARS performance



# ■ Constructed models

Performed well in all power company models.  
0.870(Kyushu ) ~ 0.953(Okinawa)

	Hokkaido	Tohoku	Tokyo	Chubu	Hokuriku	Kansai	Chugoku	Shikoku	Kyushu	Okinawa
R <sup>2</sup>	0.922	0.909	0.935	0.902	0.890	0.933	0.908	0.903	0.873	0.953
generalized R <sup>2</sup>	0.921	0.907	0.934	0.900	0.887	0.932	0.907	0.901	0.870	0.953
Number of terms	35	39	29	37	39	25	29	32	35	30
Number of predictors adopted	9	9	8	10	9	7	7	7	8	9
Number of input predictors	11	11	11	11	11	11	11	11	11	11
TEMP	○	○	○	○	○	○	○	○	○	○
HUM	-	-	-	-	-	-	-	-	-	-
SUN	○	○	○	○	○	○	○	○	○	○
WIND	-	-	-	○	○	-	-	-	○	○
RAIN	○	-	○	○	-	-	-	-	-	○
SNOW	○	○	-	-	○	-	-	-	-	-
DI	○	○	○	○	○	○	○	○	○	○
WCI	-	○	-	○	-	-	-	-	-	○
HDD	○	○	○	○	○	○	○	○	○	-
WORK%	○	○	○	○	○	○	○	○	○	○
WAKE%	○	○	○	○	○	○	○	○	○	○
SLEEP%	○	○	○	○	○	○	○	○	○	○



# Model performance

High-quality models in terms of both fitting and generalization

x-axis : Actual (MWh) y-axis : Prediction (MWh)

○ : In-sample result

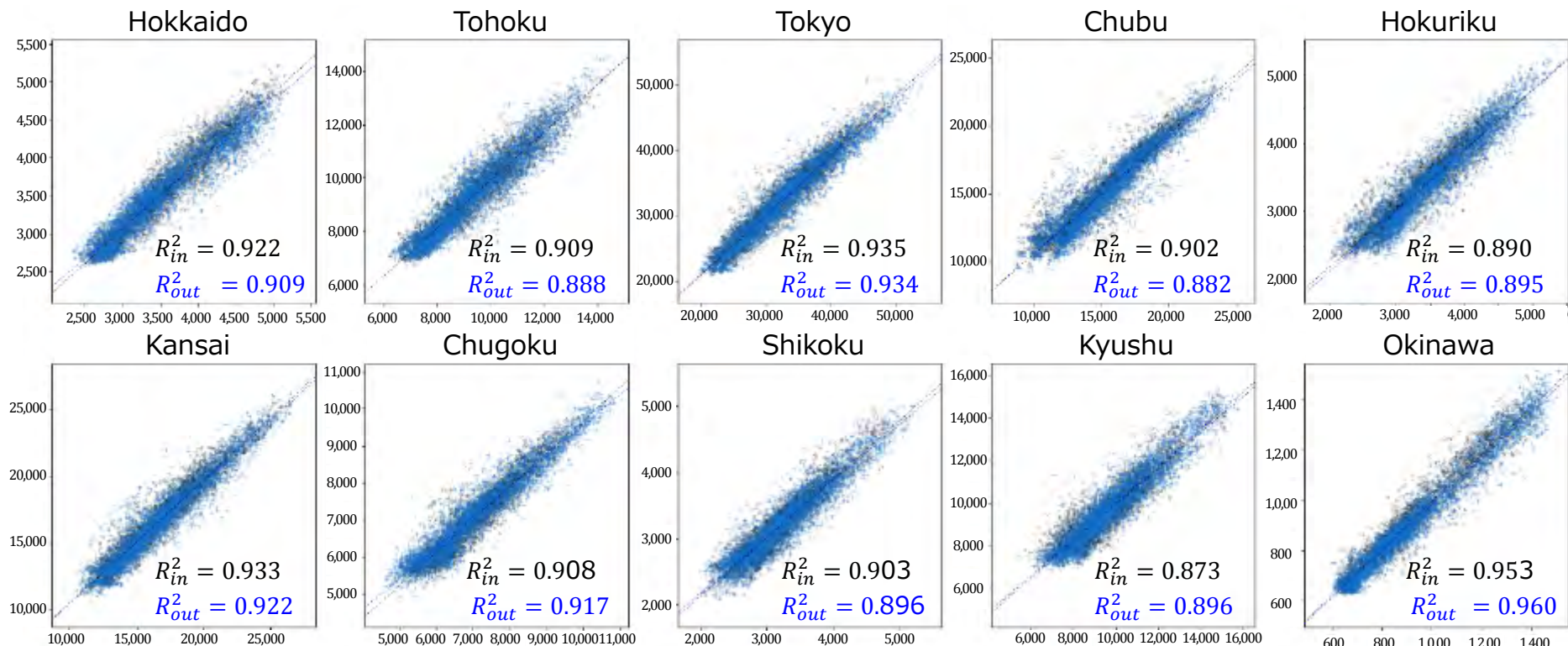
+ : Out-of-sample result

— : OLS regression line for in-sample result

..... : OLS regression line for out-of-sample result

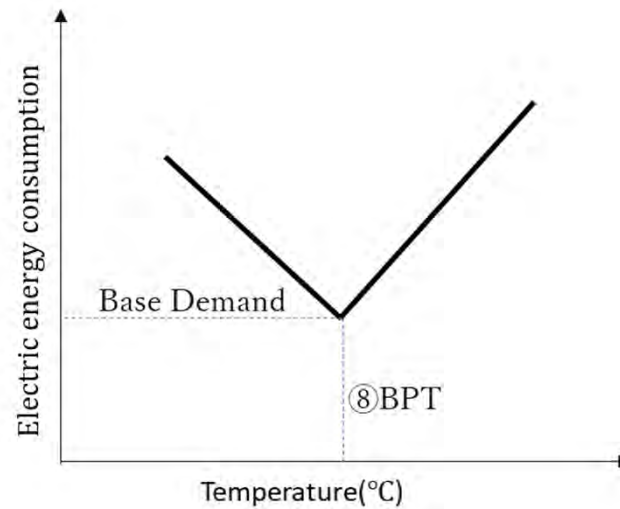
$R_{in}^2$  : The coefficient of determination of OLS (in-sample)

$R_{out}^2$  : The coefficient of determination of OLS (out-of-sample)



Observed values vs estimated values

# Simulating Temperature Response Functions



# Hourly simulation

## Settings for the simulation

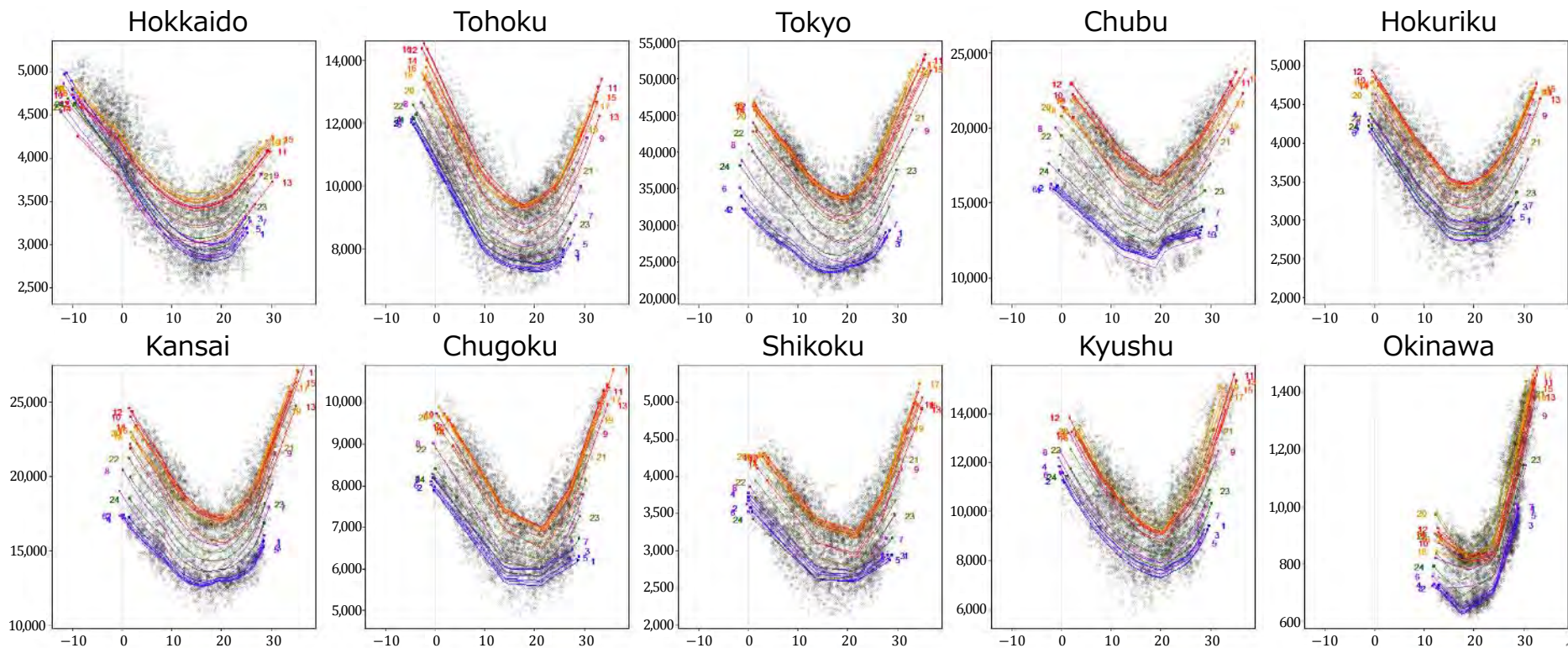
<b>Weather predictors</b> TEMP	Regular sequences of the value
<b>Weather predictors</b> HUM, SUN, WIND, RAIN, SNOW	Average values of each time period at each location in weekdays.
<b>The thermal indicators</b> DI, WCI	Calculated from the weather predictors .
<b>Holiday dummy</b> HDD	Weekdays: 0
<b>Human activity predictors</b> WORK%, WAKE%, SLEEP%	Values of each time period in weekdays.

x-axis : Temperature (°C)

y-axis : Power consumption (MWh)

○ Observation

Hourly simulation



# Simulation in day-time and night-time

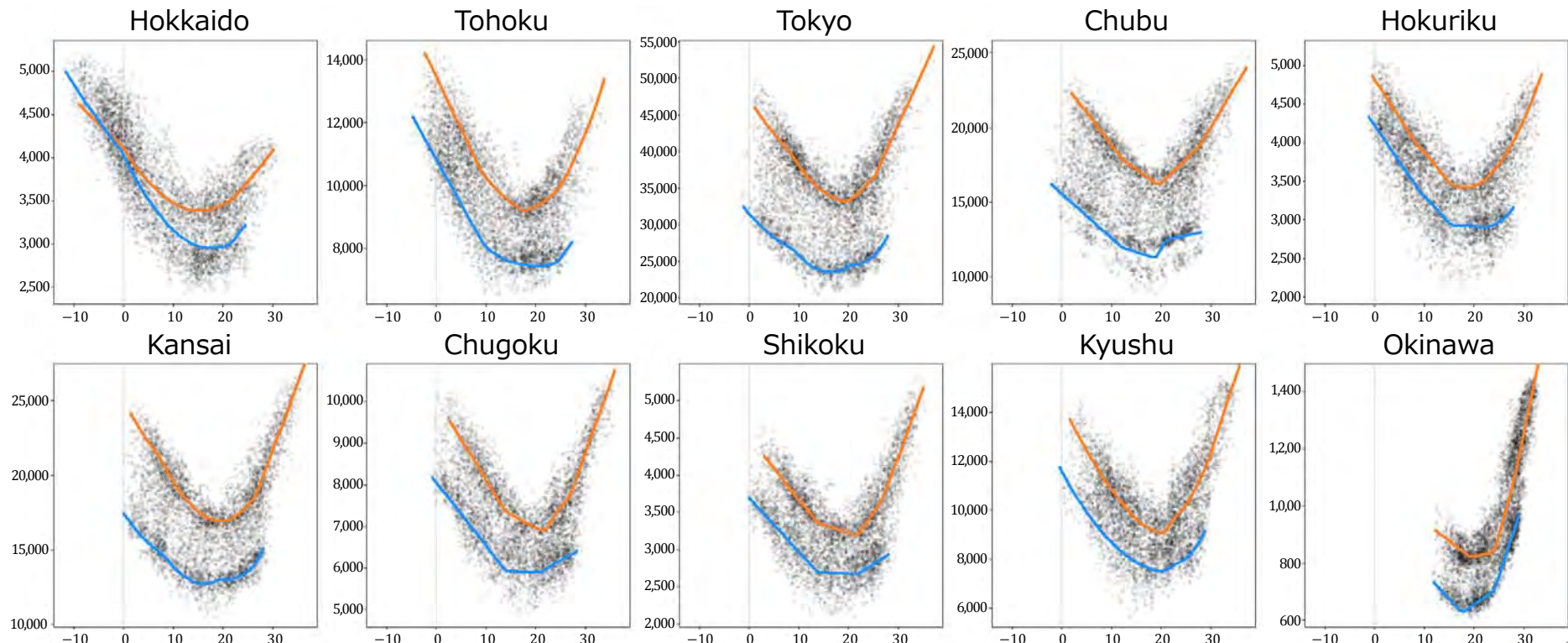
## Settings for the simulation

<b>Weather predictors</b> TEMP	Regular sequences of the value
<b>Weather predictors</b> HUM, SUN, WIND, RAIN, SNOW	Average values in day-time and night-time at each location in weekdays.
<b>The thermal indicators</b> DI, WCI	Calculated from the weather predictors .
<b>Holiday dummy</b> HDD	Weekdays: 0
<b>Human activity predictors</b> WORK%, WAKE%, SLEEP%	Average values during day-time and night-time in weekdays.

x-axis : Temperature (°C)

y-axis : Power consumption (MWh)

- Observation
- Day-time simulation (from 10:00 to 18:00)
- Night-time simulation (from 1:00 to 5:00)



# ■ Approximation

“Temperature response functions”  
are approximated by **piecewise  
linear function** using MARS.

x-axis : Temperature (°C)

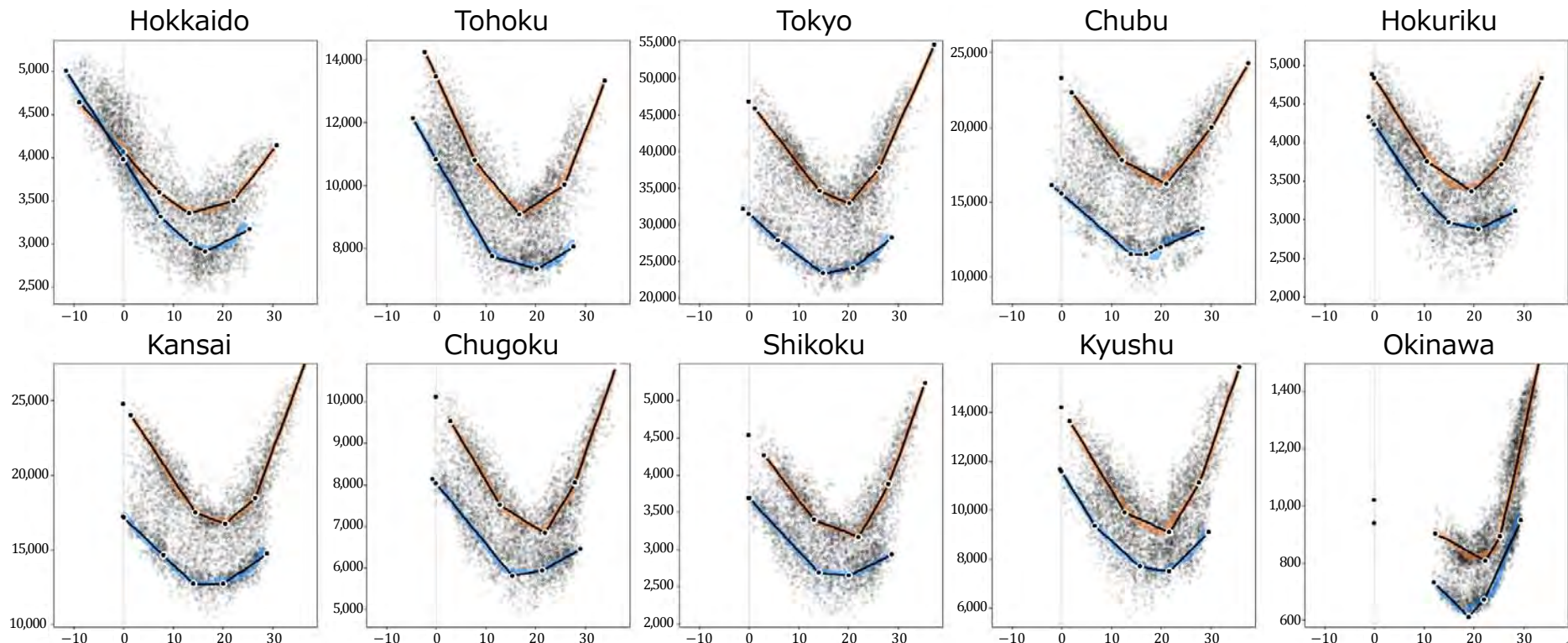
y-axis : Power consumption (MWh)

○ Observation

— Day-time simulation

— Night-time simulation

— Approximate function ● breakpoints



# ■ Approximate function

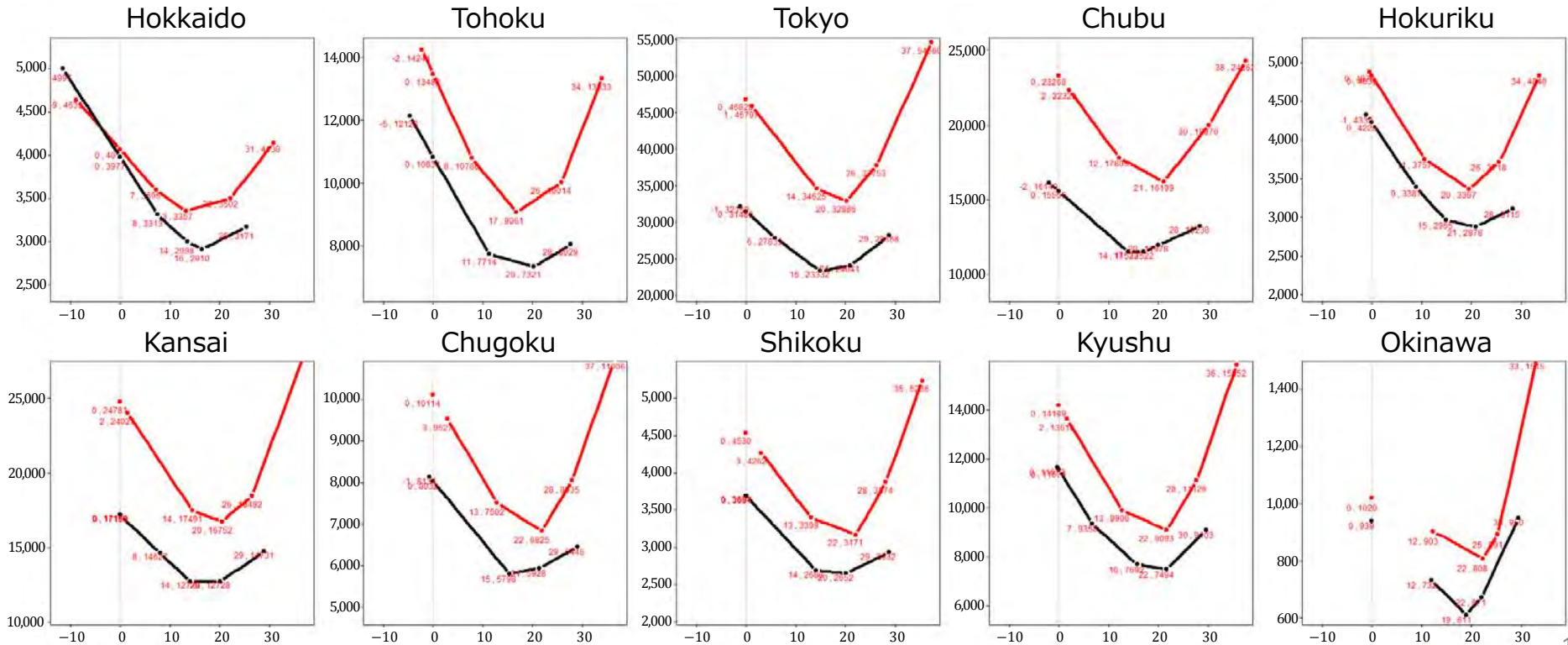
**Parameters**(the coordinates of breakpoints, the coefficients of each linear function) **can be obtained from the piecewise linear function**



**Provide the parameters to other models**

x-axis : Temperature (°C)  
y-axis : Power consumption (MWh)

- Observation
- Approximate function for day-time
- Approximate function for night-time



# ■ The effect of humidity on power consumption

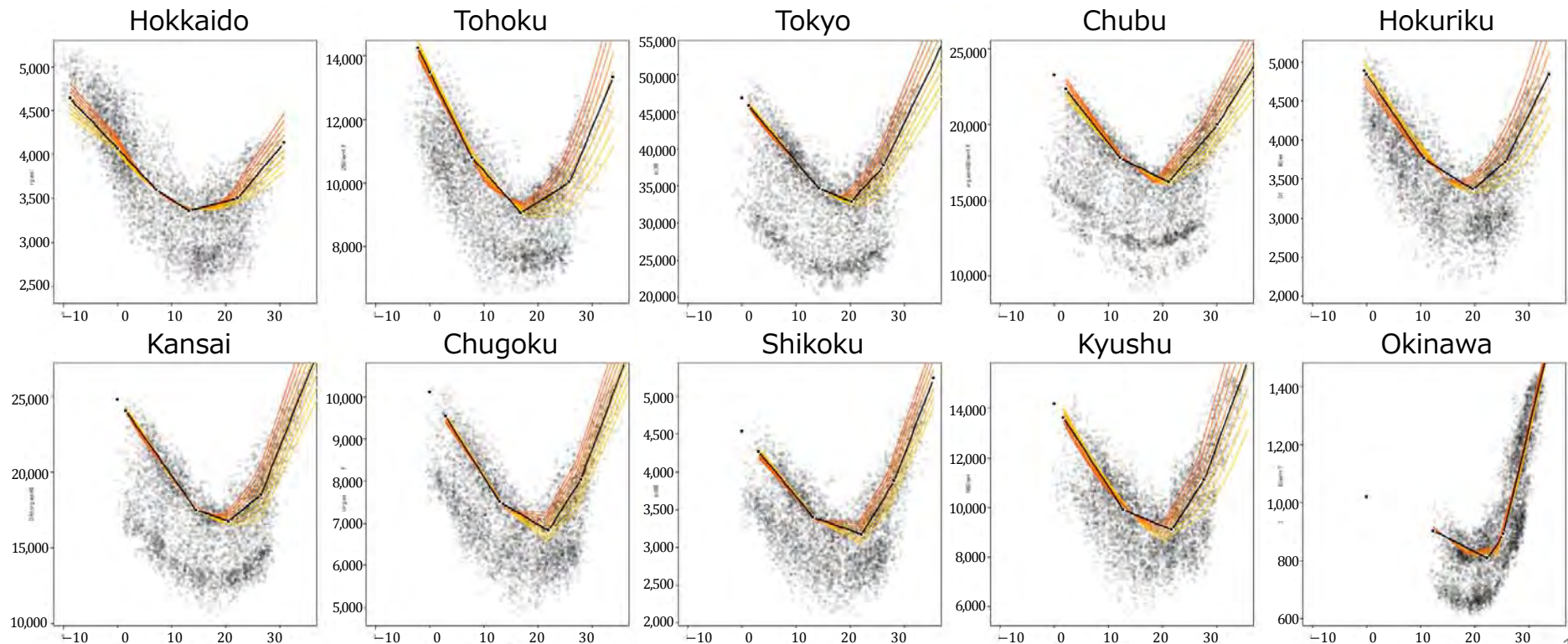
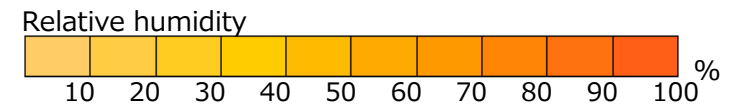
## Settings for the simulation

<b>Weather predictors</b> TEMP,HUM	Regular sequences of the value
<b>Weather predictors</b> SUN, WIND, RAIN, SNOW	Average values in day-time at each location in weekdays.
<b>The thermal indicators</b> DI, WCI	Calculated from the Weather predictors .
<b>Holiday dummy</b> HDD	Weekdays: 0
<b>Human activity predictors</b> WORK%, WAKE%, SLEEP%	Values for each time period in weekdays.

x-axis : Temperature (°C)

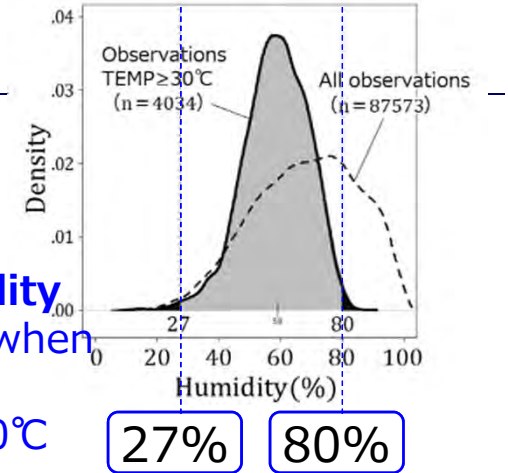
y-axis : Power consumption (MWh)

○ Observation



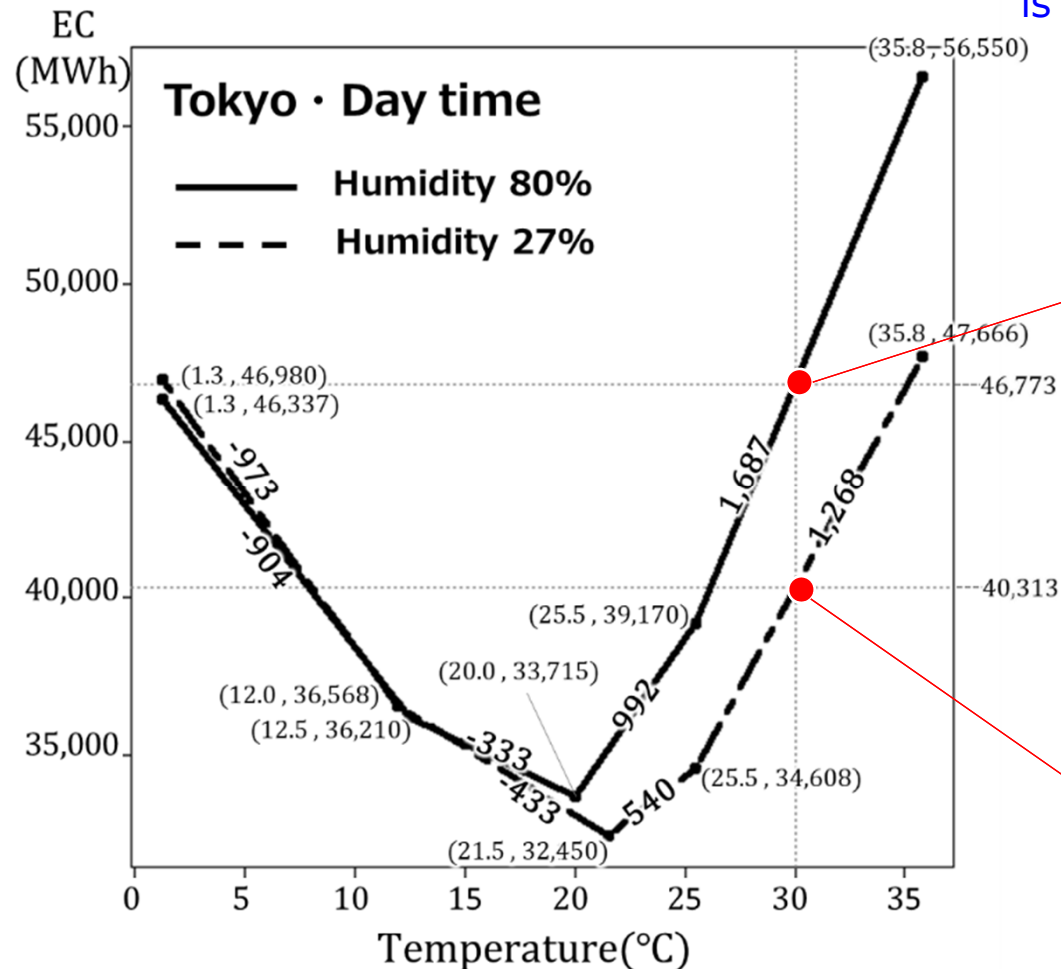
# ■ The effects of humidity in detail

## A simulation for Tokyo in daytime as an example



An actual **humidity range** in Tokyo when the temperature is higher than 30°C

**27%** **80%**



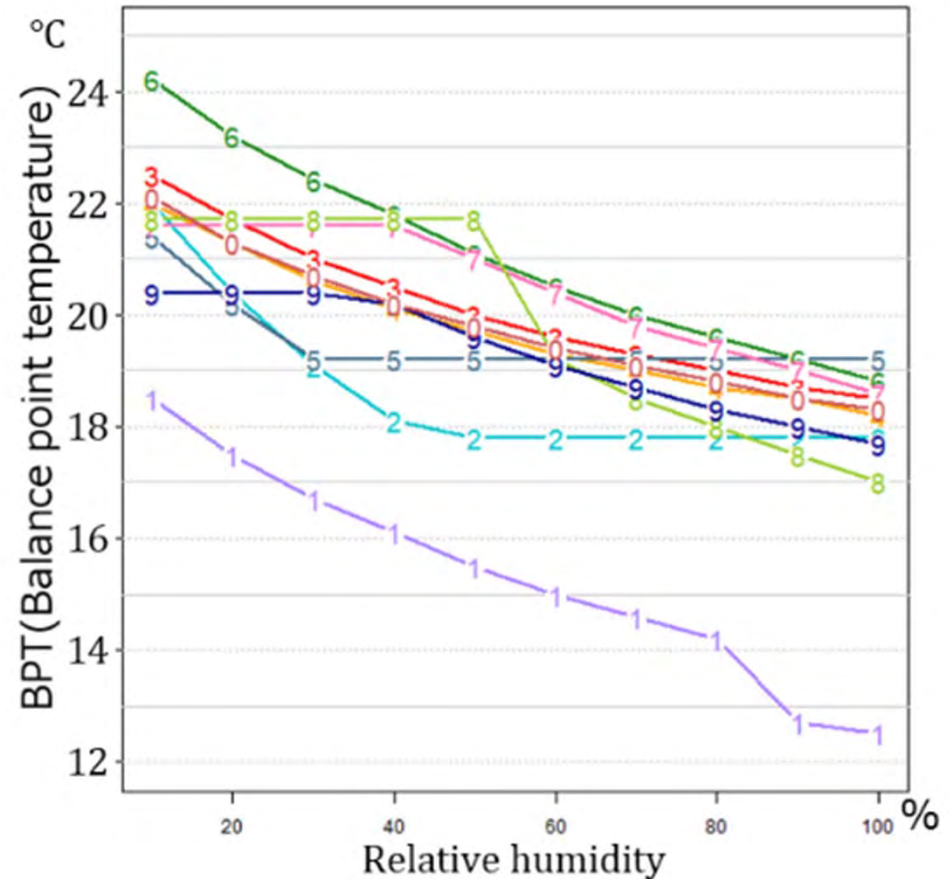
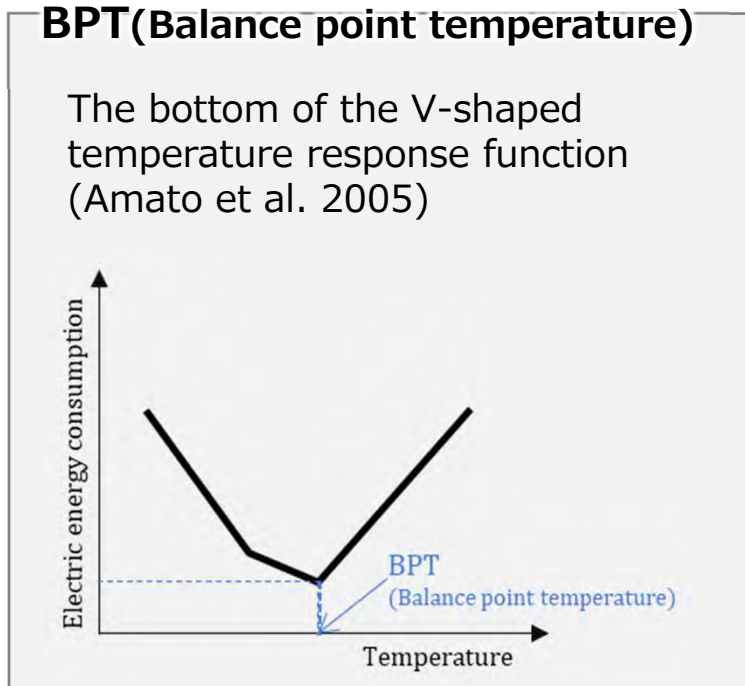
Temperature 30°C  
Humidity **80%**

Power consumption reduced by **13.8%**.

Temperature 30°C  
Humidity **27%**



# ■ BPT(Balance point temperature)



## BPT decrease as humidity rises

:Under the conditions wherein the **humidity is high**, the power consumption for cooling **begins to increase at lower temperatures**.

- |            |             |
|------------|-------------|
| 1 Hokkaido | 6 Kansai    |
| 2 Tohoku   | 7 Chugoku   |
| 3 Tokyo    | 8 Shikoku   |
| 4 Chubu    | 9 Kyusyu    |
| 5 Hokuriku | 0 Okinawans |

we proposed a series of methods to understand the relationship between **weather conditions** and the **hourly electricity demand**

## Summarized results

- The constructed models are of high-quality in terms of **1) fitting, 2) generalization capability, and 3) simulating accurate temperature response functions**
- **Two different Temperature Response Functions** were identified in a day; for day-time (from 10:00 to 18:00) and for night-time (from 1:00 to 5:00).
- **Humidity affects electricity consumption significantly** when temperature is high
- Under the condition wherein the humidity is high, the power consumption for cooling begins to increase at lower temperatures.



## Suggestions

- **The proposed method is recommended for identifying temperature response functions; especially the consideration of multiple factors are important.**
- **The effect of humidity should not be ignored.**

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# Thank you

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I always welcome your critical comments, suggestions, and corrections.