



# **Koopman operator techniques applied to data analytics in transmission systems**

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# Outline of Presentation

## Koopman operator techniques applied to data analytics in transmission systems

- Motivation
- Synchrophasor measurement in Japan: A NEDO project
- Koopman mode decomposition
- Inertia estimation of Japan's power systems via ambient synchrophasor data
- Wrap-up

$$y(t) = \sum_{j=1}^{\infty} \exp(\nu_j t) V_j, \quad t \geq 0$$

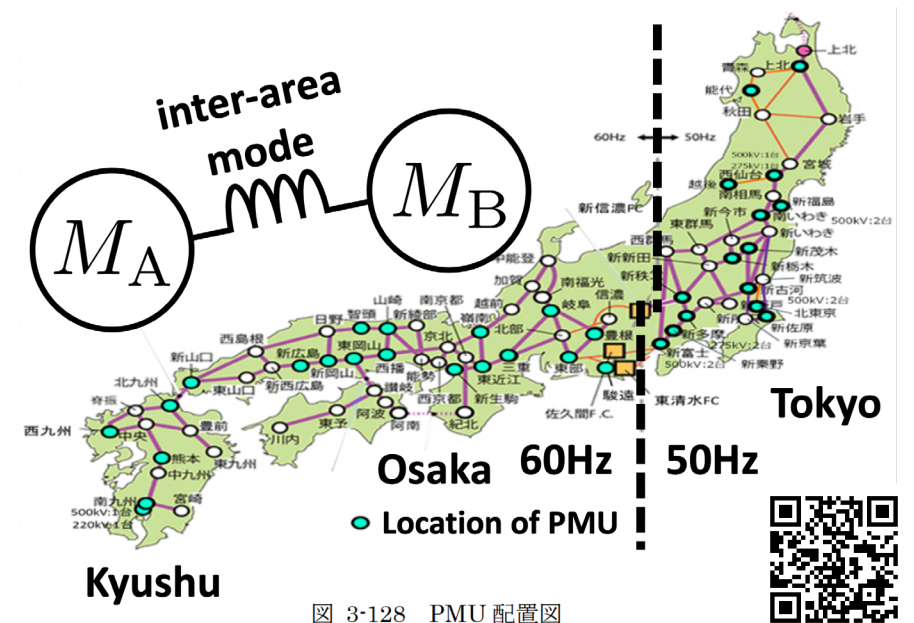
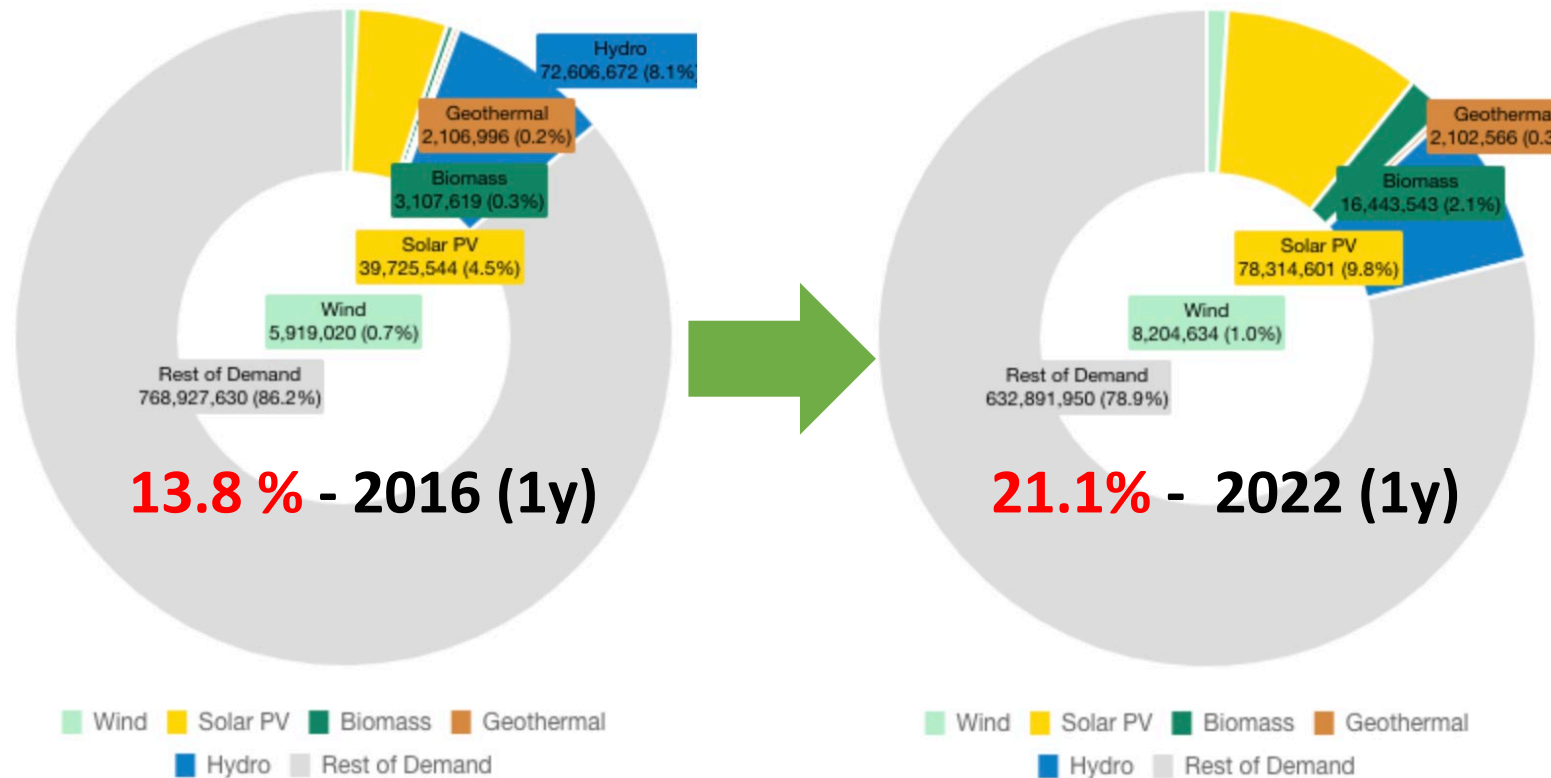


図 3-128 PMU 配置図

# Motivation from Japan's systems

## Penetration of renewables



- Expected to increase to **36-38 %** in the 2030s
- Solar PV: increase by 50 billion kWh
- Offshore wind: increase by + 1 billion kWh
- Inevitable **reduction of inertia** provided by thermal plants

from <https://isep-energychart.com/en/>

# NEDO project (2019-2021)

## Synchrophasor measurement

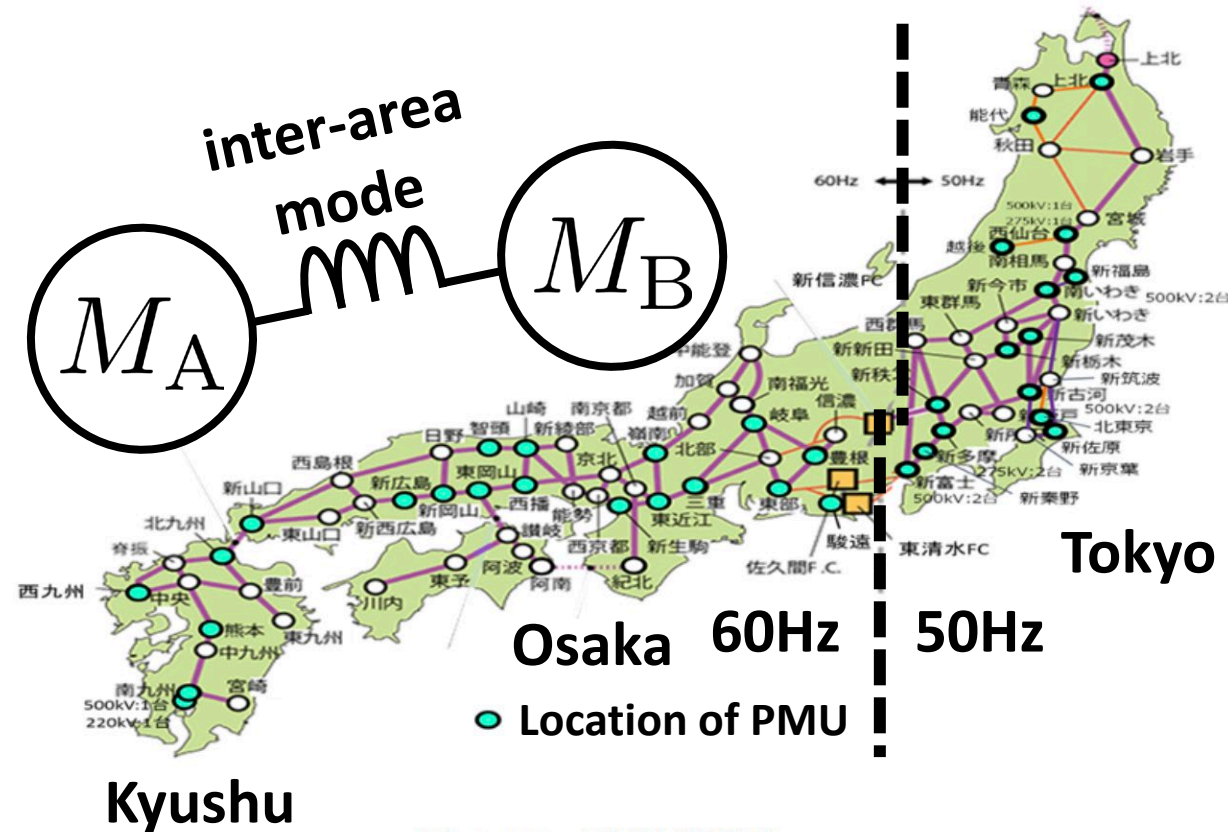


図 3-128 PMU 配置図

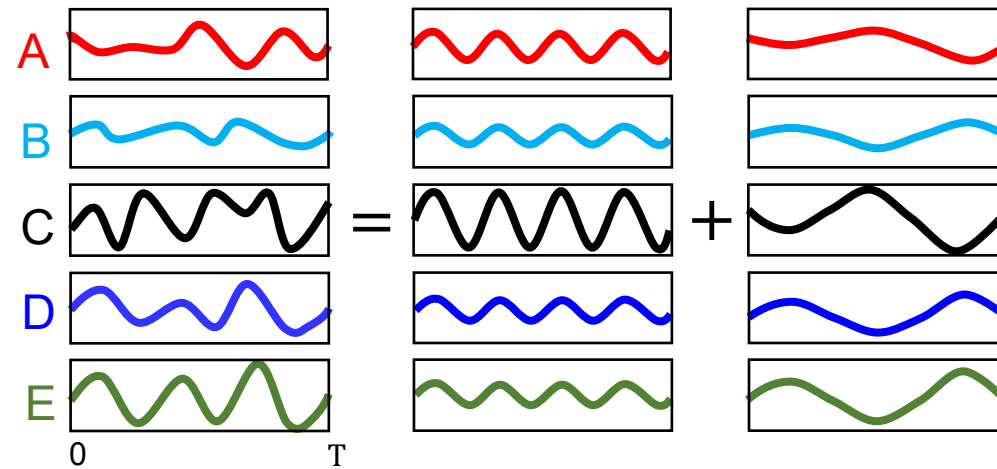
from the official report (in Japanese)

- Mainly led by Tokyo Electric Power Company Holdings, Inc., and Kyushu Institute of Technology
- Development of basic technology to address the problem of **reduced system inertia**
- Totally **40 PMUs** installed at 500kV or 275kV substations



# Koopman mode decomposition

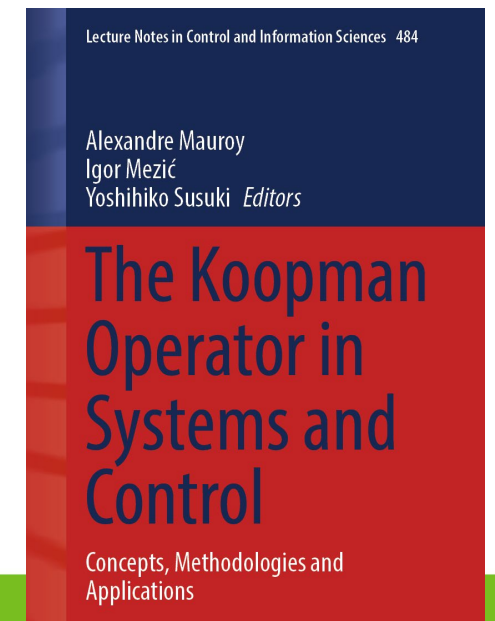
(Refs.) Mezic (2005)  
Rowley *et al.* (2009)



multivariate time series = oscillatory mode (single-frequency)

$$\mathbf{y}(t) = \sum_{j=1}^{\infty} \exp(\nu_j t) \mathbf{V}_j, \quad t \geq 0$$

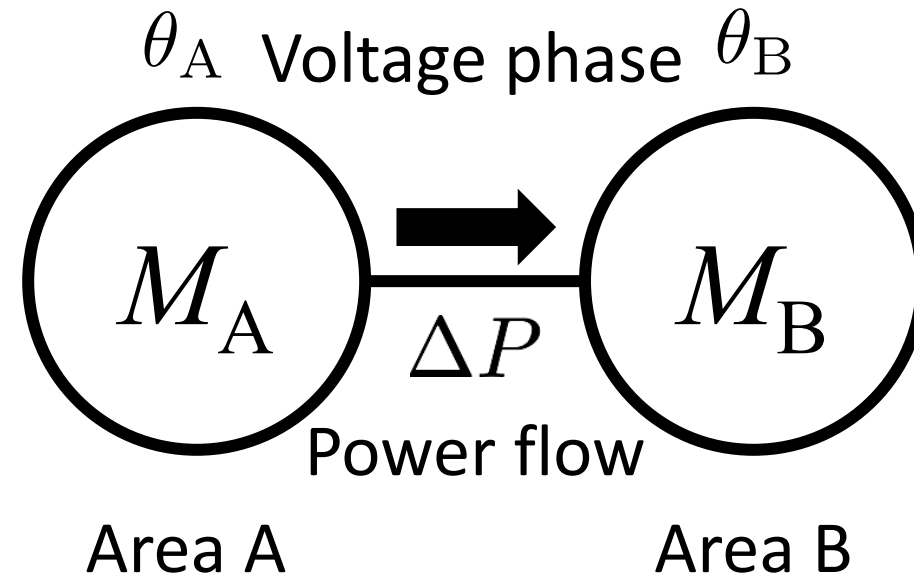
- Guided by the **Koopman operators** for nonlinear systems
- **Dynamic Mode Decomposition** as a standard algorithm
- Utilized in power system performance assessment
  - Susuki & Mezic (2011); Barocio *et al.* (2015); and many



# Inertia estimation 1/4

## Underlying model

- Standard swing equations assumed
- Two time-series utilized for the estimation:
  1. Frequency deviations (COI)
  2. Exchanged power flow



$$M_A \frac{d^2}{dt^2} \theta_A = \Delta P$$

$$M_B \frac{d^2}{dt^2} \theta_B = -\Delta P$$

$$M_A \frac{d}{dt} \omega_A = \Delta P$$

$$M_B \frac{d}{dt} \omega_B = -\Delta P$$

# Inertia estimation 2/4

## Two steps

1. Compute **Koopman modes and eigenvalues** by applying a **DMD** to time-series data on frequency deviations and exchanged power flow

$$\begin{bmatrix} \Delta\omega_A(t) \\ \Delta\omega_B(t) \\ \Delta P(t) \end{bmatrix} = \sum_{j=1}^{\infty} \exp(\nu_j t) \begin{bmatrix} V_j^{\Delta\omega_A} \\ V_j^{\Delta\omega_B} \\ V_j^{\Delta P} \end{bmatrix}$$

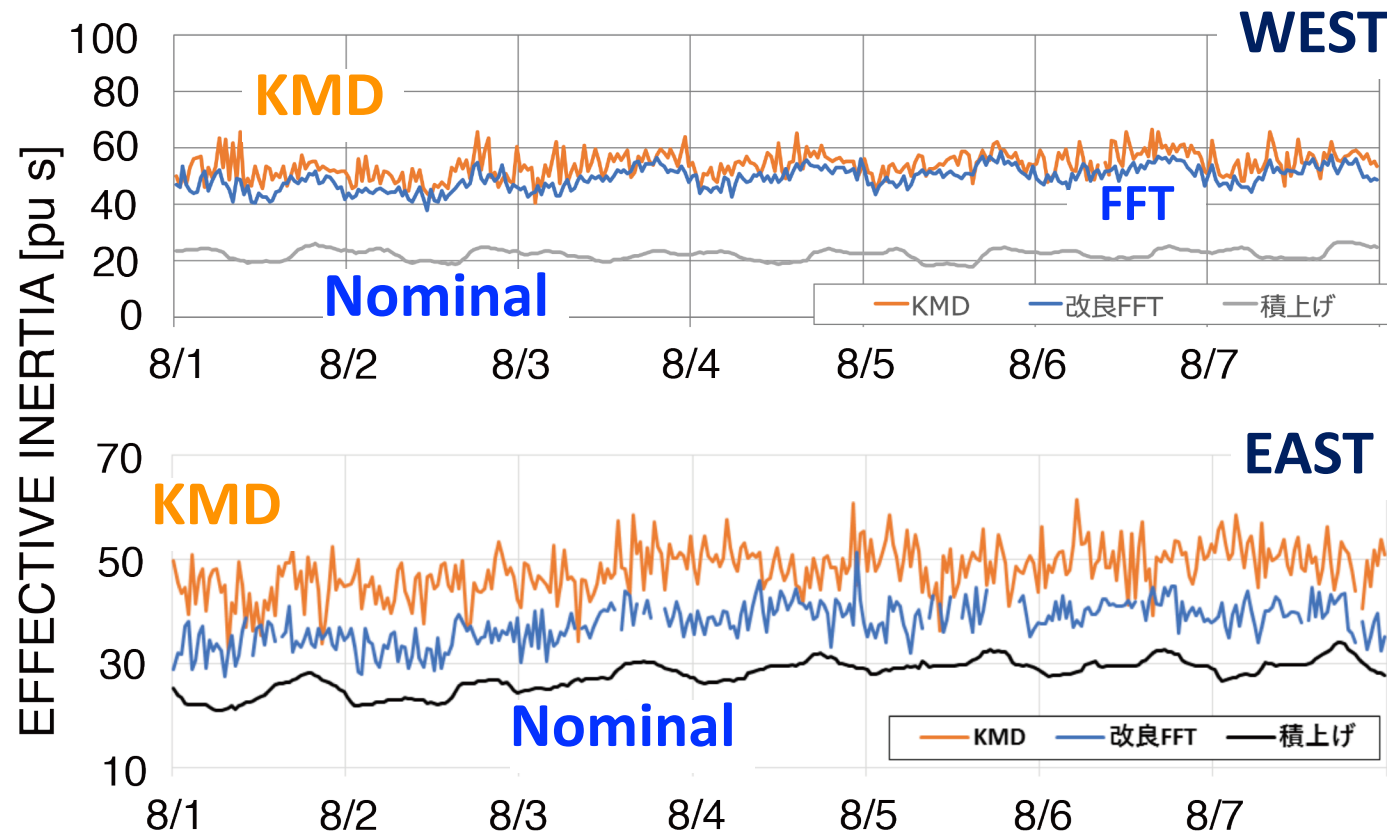
2. Estimate the inertia constants from:

$$M_A^j := \frac{|V_j^{\Delta P}|}{|\nu_j V_j^{\Delta\omega_A}|}, \quad M_B^j := \frac{|V_j^{\Delta P}|}{|\nu_j V_j^{\Delta\omega_B}|}$$

- Note: it depends on the choice of modes, here, **the inter-area mode**.

# Inertia estimation 3/4

## Result and comparison



- FFT as another method of the estimation
- Nominal as the sum of inertia constants of online / offline generators
- Similarity in the estimation
- Difference caused by non-visible generators in consumer sides and control effects etc.

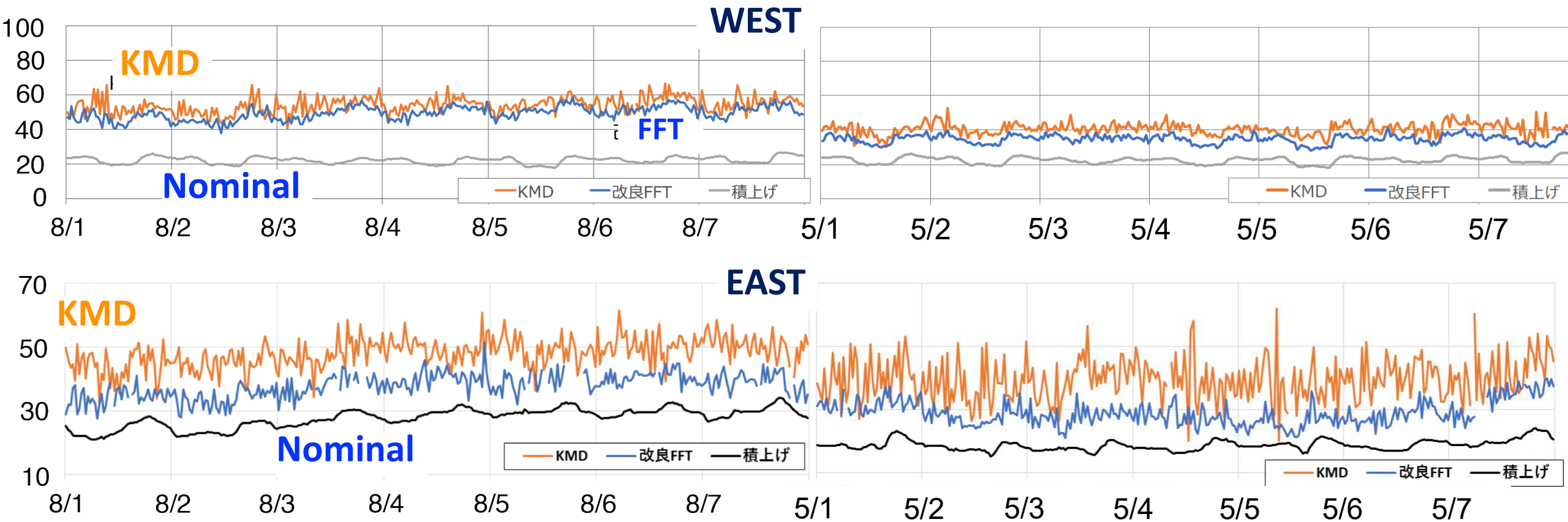


from the official report (in Japanese)



# Inertia estimation 4/4

## Dependence on loading conditions

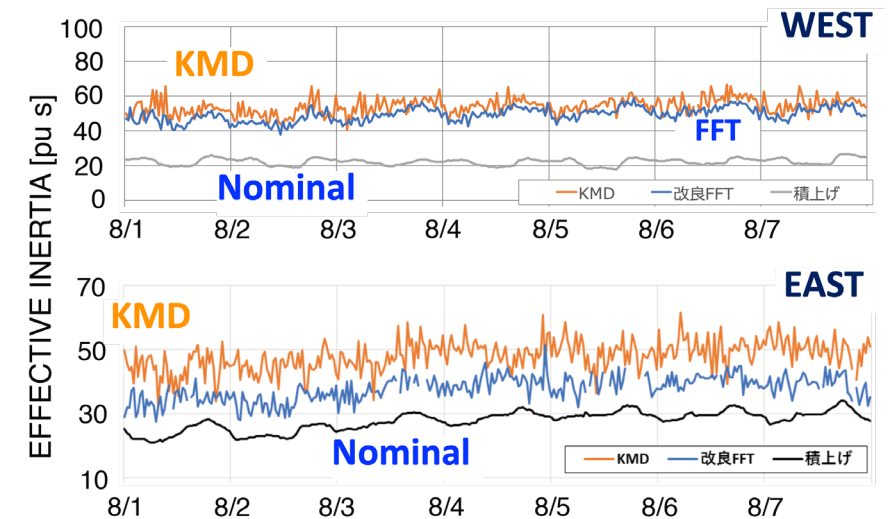
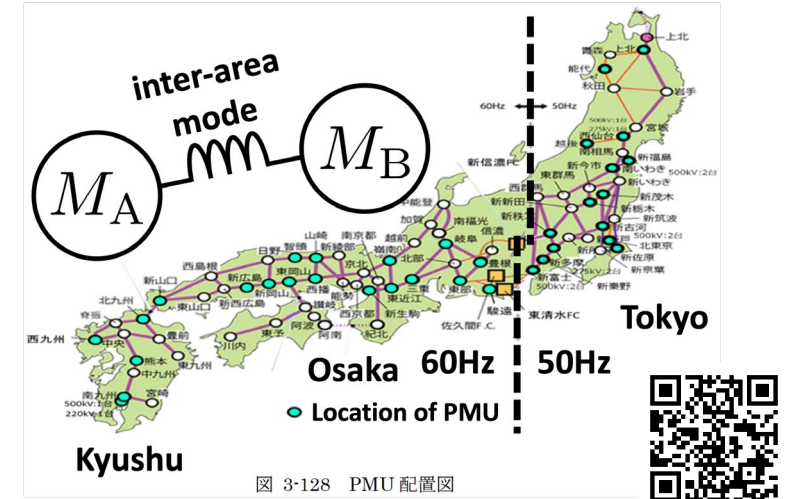


from the official report (in Japanese)

# Summary - takeaways

## Koopman operator techniques applied to data analytics in transmission systems

- KMD provides a fully-data-driven technique of inertia estimation from synchrophasor data and power-flow data.
- Non-visible generators and control effects have a non-negligible impact.



# Thank you for your attention!

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