Weather Impact on Electric Power Load and Electric Power Load Forecasting Model Considering Weather Forecasting Uncertainties

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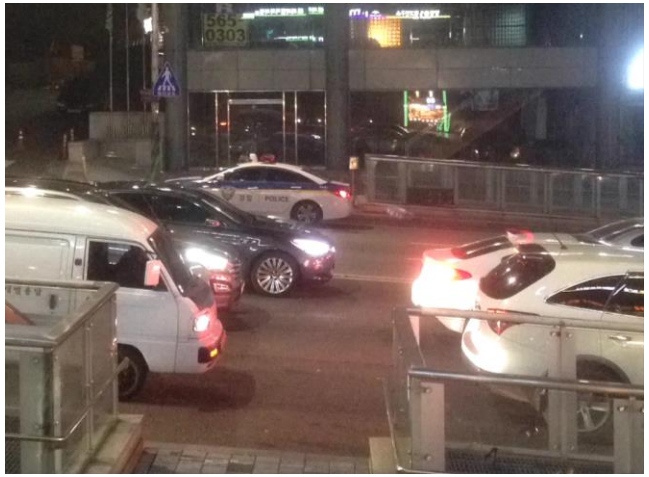
There are known knowns.

There are known unknowns.

But there are also unknown unknowns.

Donald Rumsfeld

Civilization, Climate Change, and Electricity



Of the Power, For the Power, By the Power

In Korea,

- Blackout in 2011 and economic damage
- Increasing social interests on renewable energy to replace nuclear power plants.
- About 67% increases of electrical power load during the last 10 years (1st in OECD countries)

- It is important to forecast electric power load for operational power exchange and carbon emission reduction.
  - ✓ Air temperature for electrical power load forecasting.
  - ✓ Wind and insolation for renewable energy forecasting

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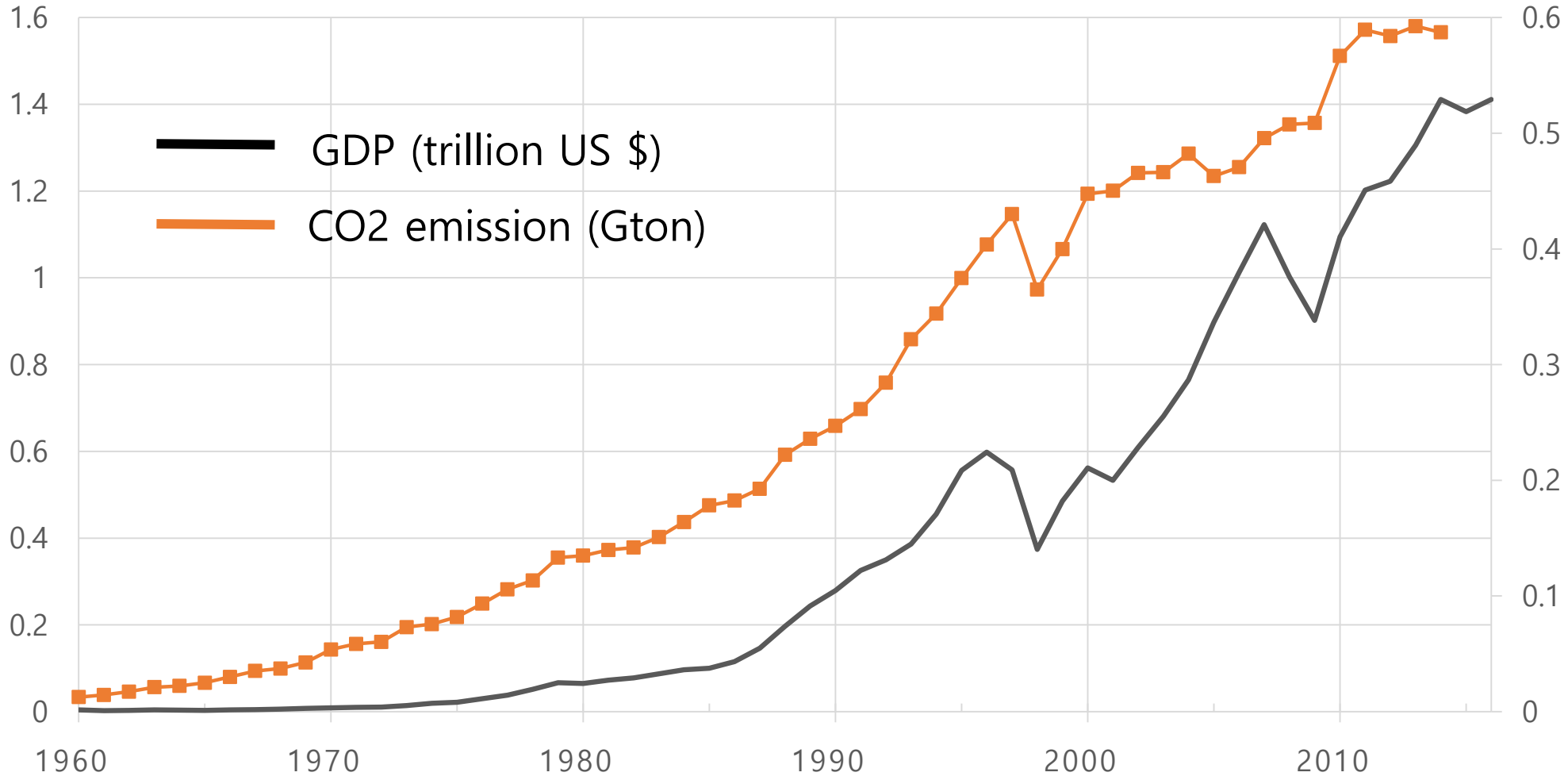
Electric power load

1. Long term variability [~ years] depends on economic growth rate.
2. Short-term and mid-term variabilities [~ daily, monthly] depend on air temperature.

Source: World Bank



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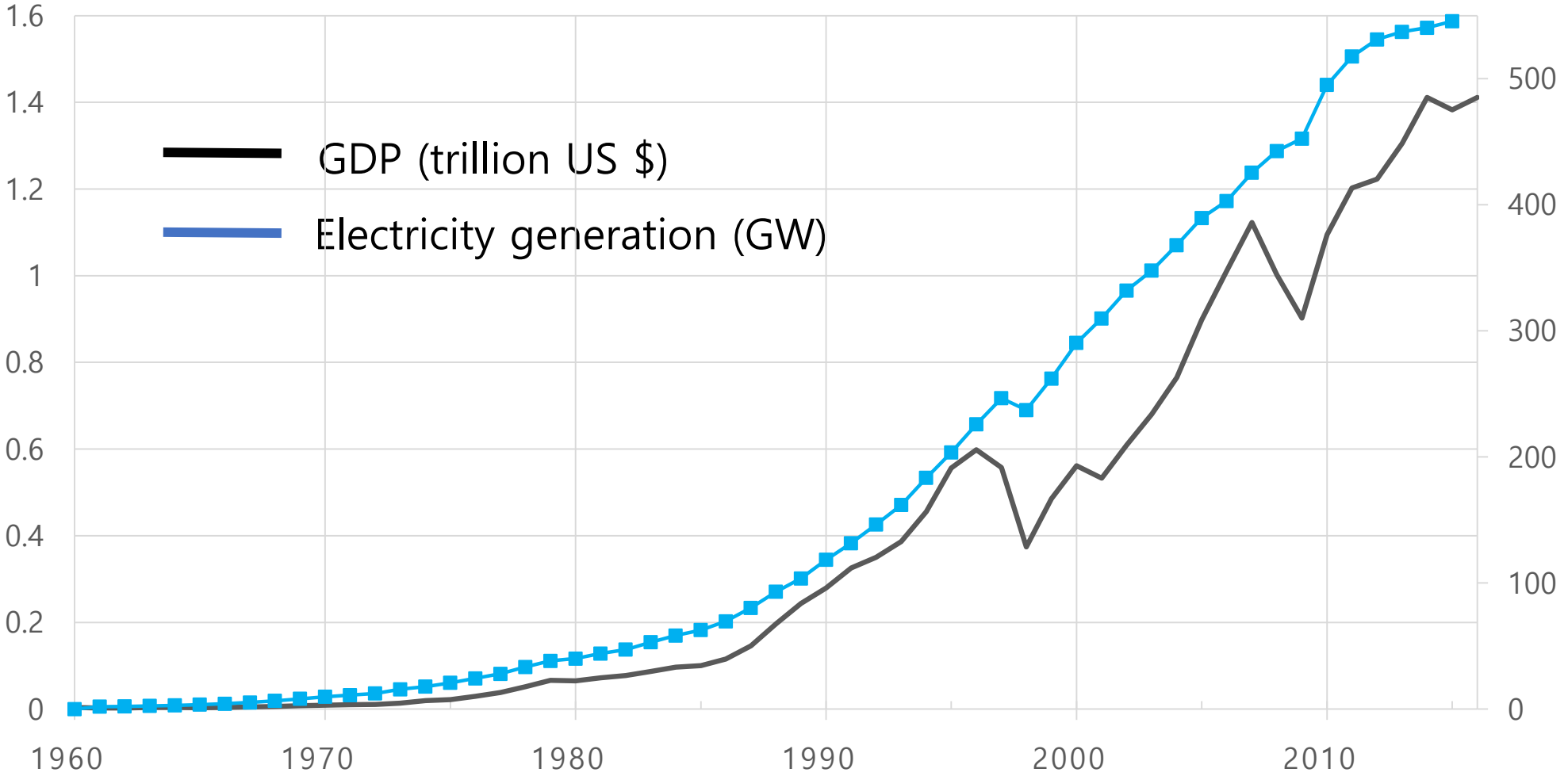
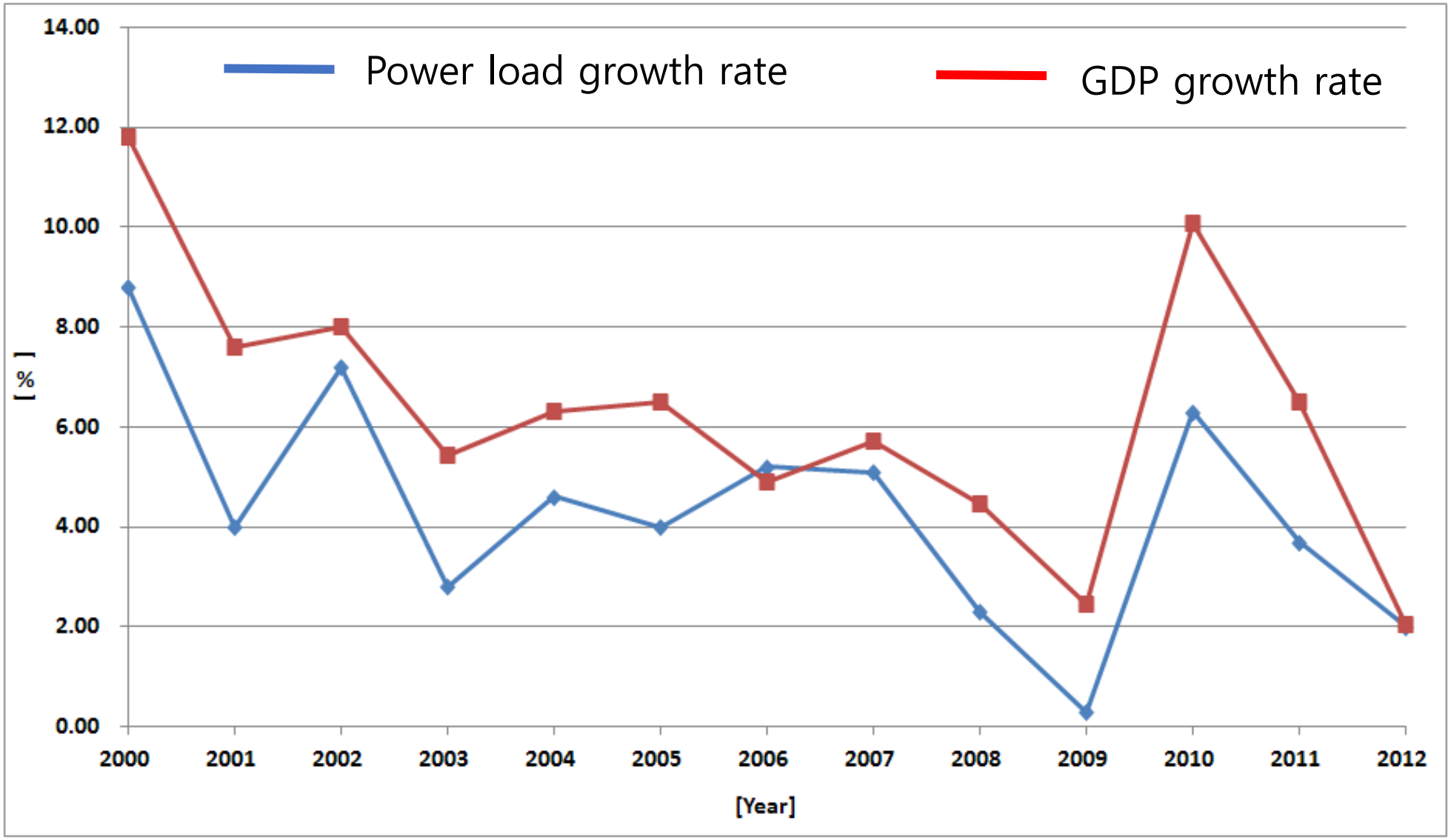
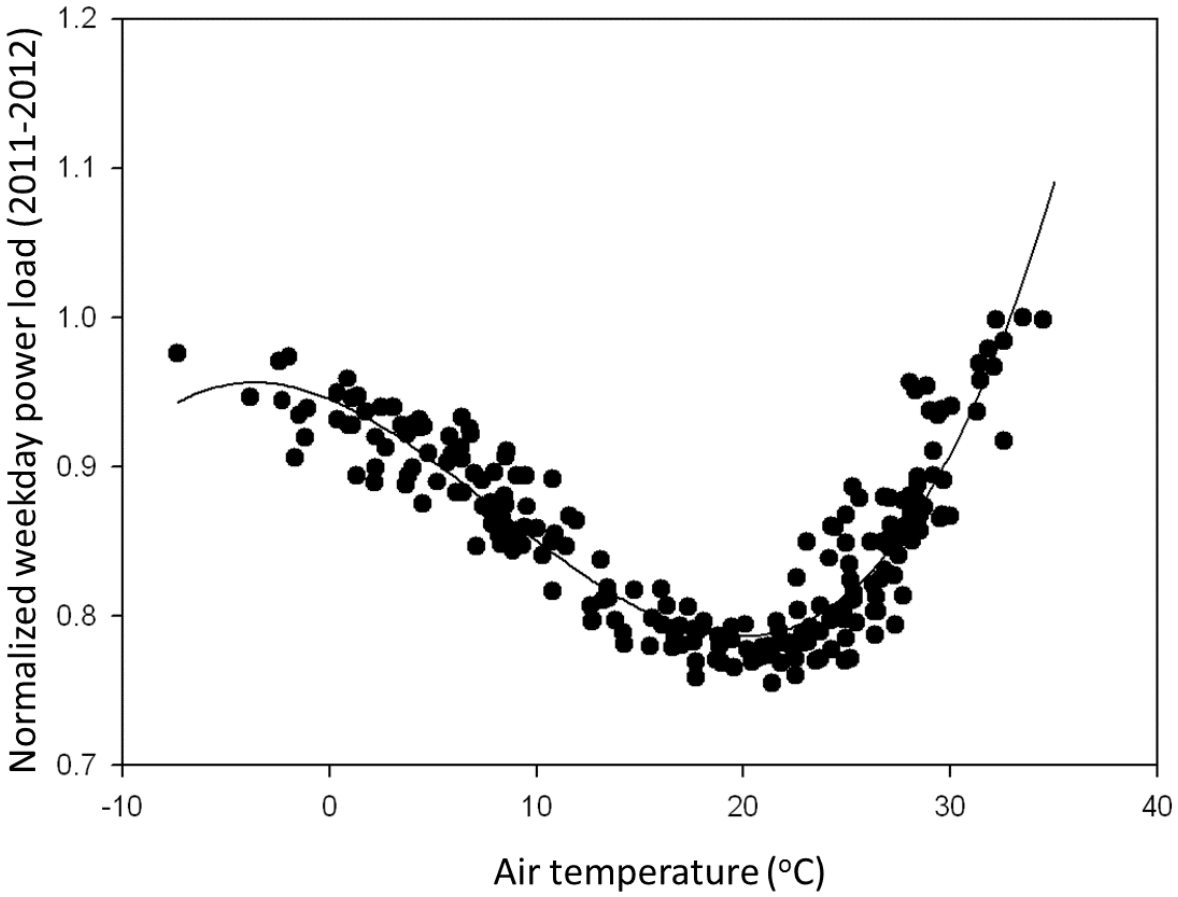
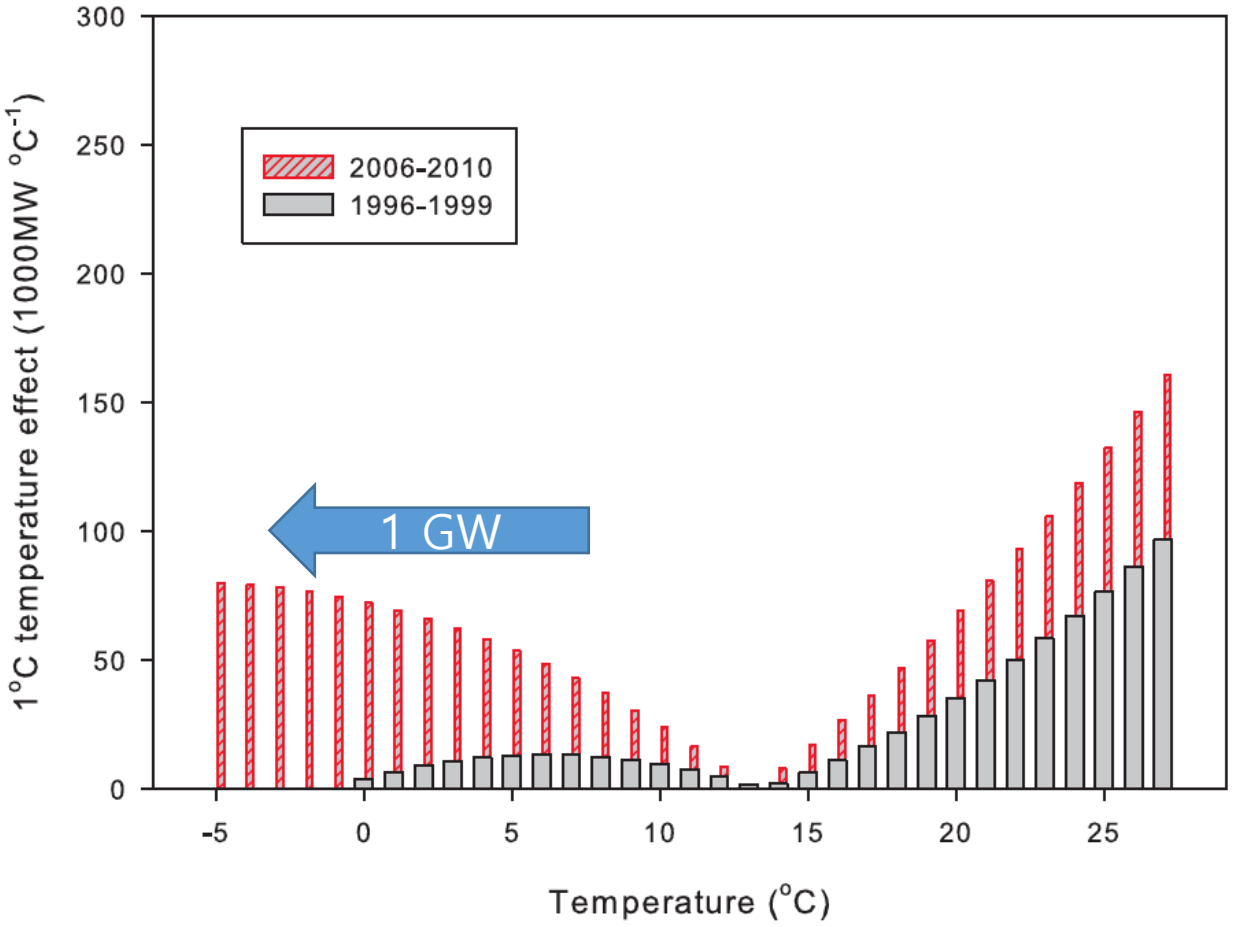


Electric power load: Long term variation



Electric power load: short- and mid-term variation





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Motivation

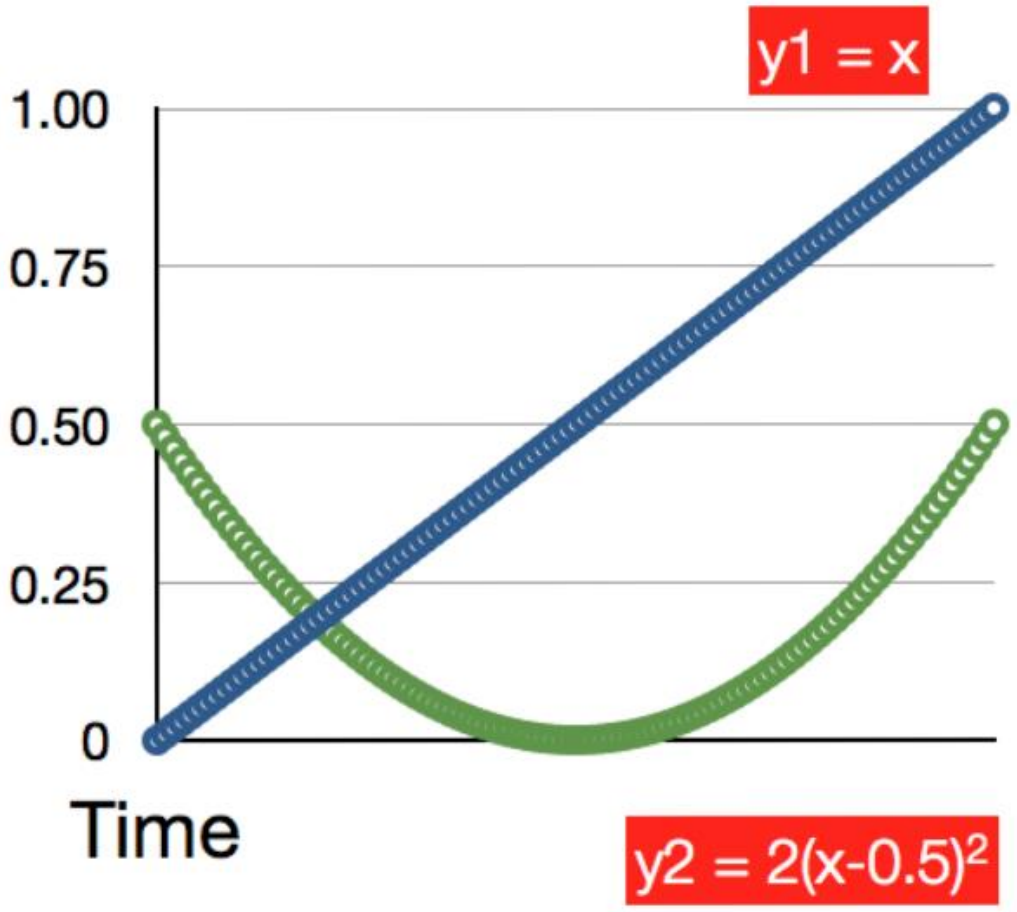
- **Weather impacts on electricity**
  - ✓ Temperature sensitivity has been reported in many studies and all operational electricity forecasting methods are considering this sensitivity.
  - ✓ Other meteorological conditions?
  - ✓ Meteorological variables are covarying and not independent. Direct and indirect impacts on power load are not easily separated. Traditional statistical approach may be inapplicable.
- **Electric power load forecasting**
  - ✓ Current weather forecasting is inappropriate to power load forecasting especially for short-term load forecasting.
  - ✓ How can we handle uncertainties in weather forecasting and psychological behaviors in power load forecasting system?

Weather Impact on Electric Power Load

Partial phase synchronization index with Wavelet transform

(Hong and Lee, 2015, Meteorol. Appl.)

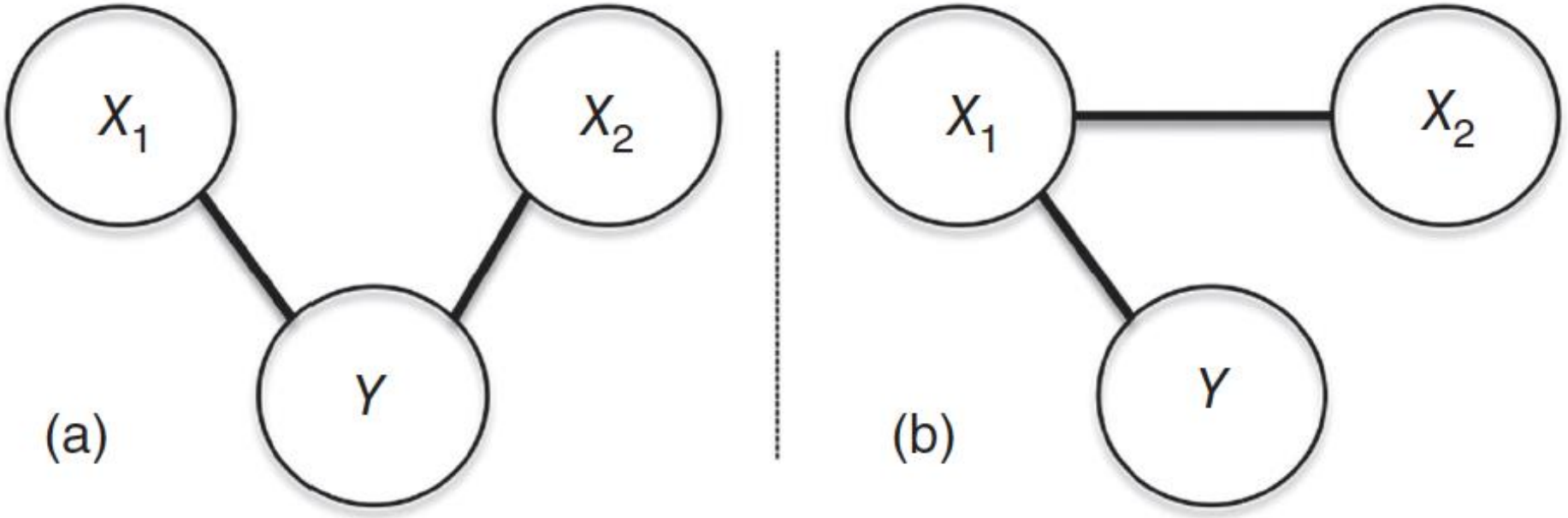
Pitfall of a linear correlation coefficient



Correlation coefficient of ZERO

- Global Analysis
- Linearity

Pitfall of a linear correlation coefficient



Example of the direct and indirect coupling of three variables: (a) $\mathbf{X}_1$ and $\mathbf{X}_2$ are directly correlated with **Y**, (b) $\mathbf{X}_2$ has indirect correlation with **Y** through $\mathbf{X}_1$.

Methods (1) Weather impacts on power load

Global analysis for the Linear system

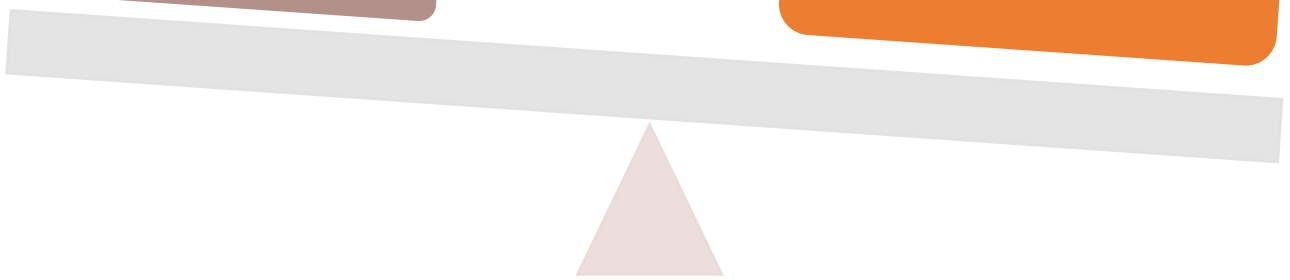
Localized analysis for the Nonlinear system

Partial correlation

Hilbert transform

Partial phase synchronization index

Wavelet transform



Phase analysis
(Shelter et al., 2006; Hong and Kim, 2015)

$$V(t) = X(t) + iX_i(t) = A(t)\,e^{i\Phi(t)} = A(t) \times Q(t)$$

$$P_{Q_k Q_l}(\omega) \propto \sum_t Q_k(t)\,e^{-i\omega t} \sum_t Q_l(t)^* \cdot e^{i\omega t}$$

$$= \sum_{t,t'} e^{i(\Phi_k(t) - \Phi_l(t-t'))} \cdot e^{-i\omega t'}$$

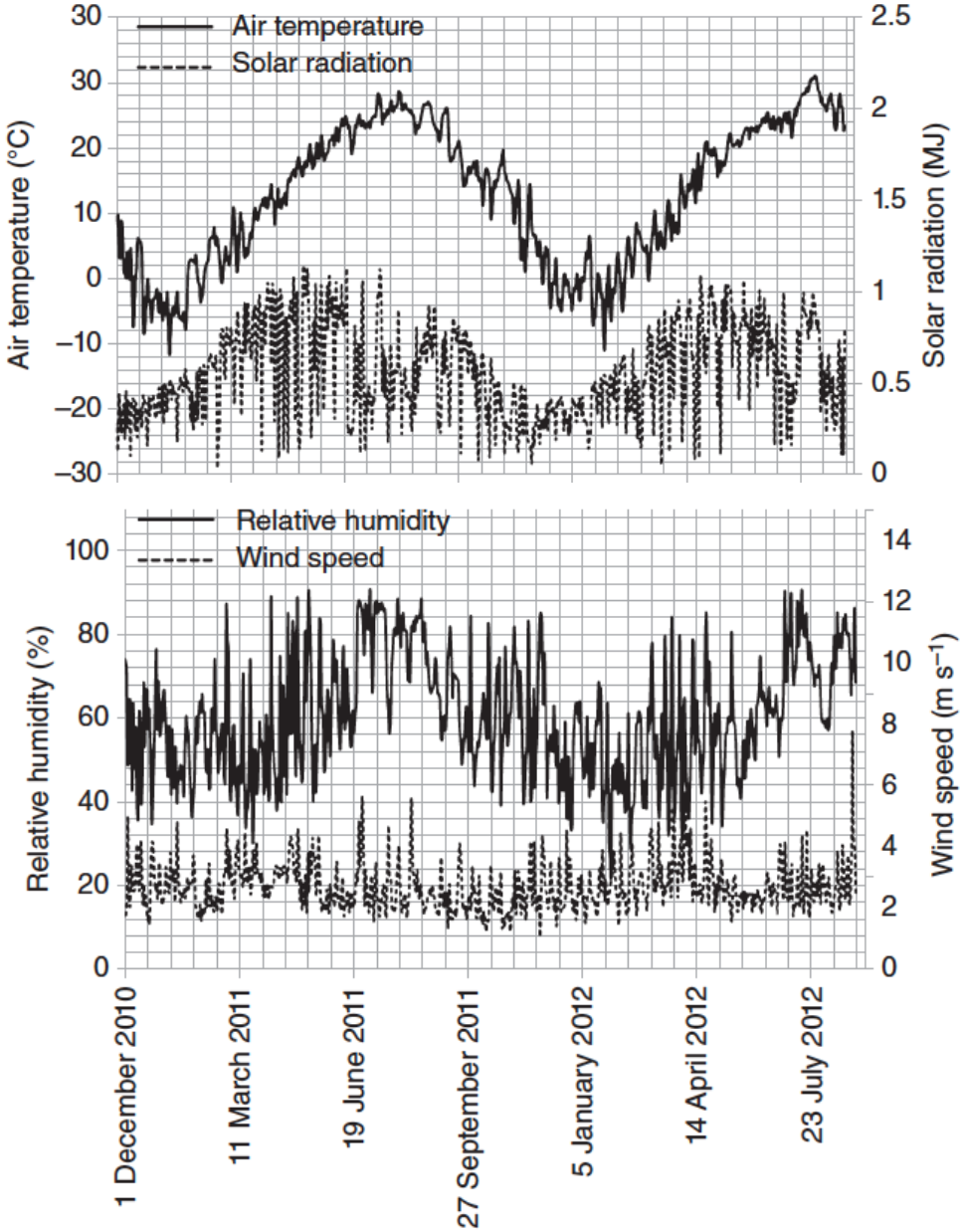
$$R_{k,l} = c \sum_\omega P_{Q_k Q_l}(\omega)$$

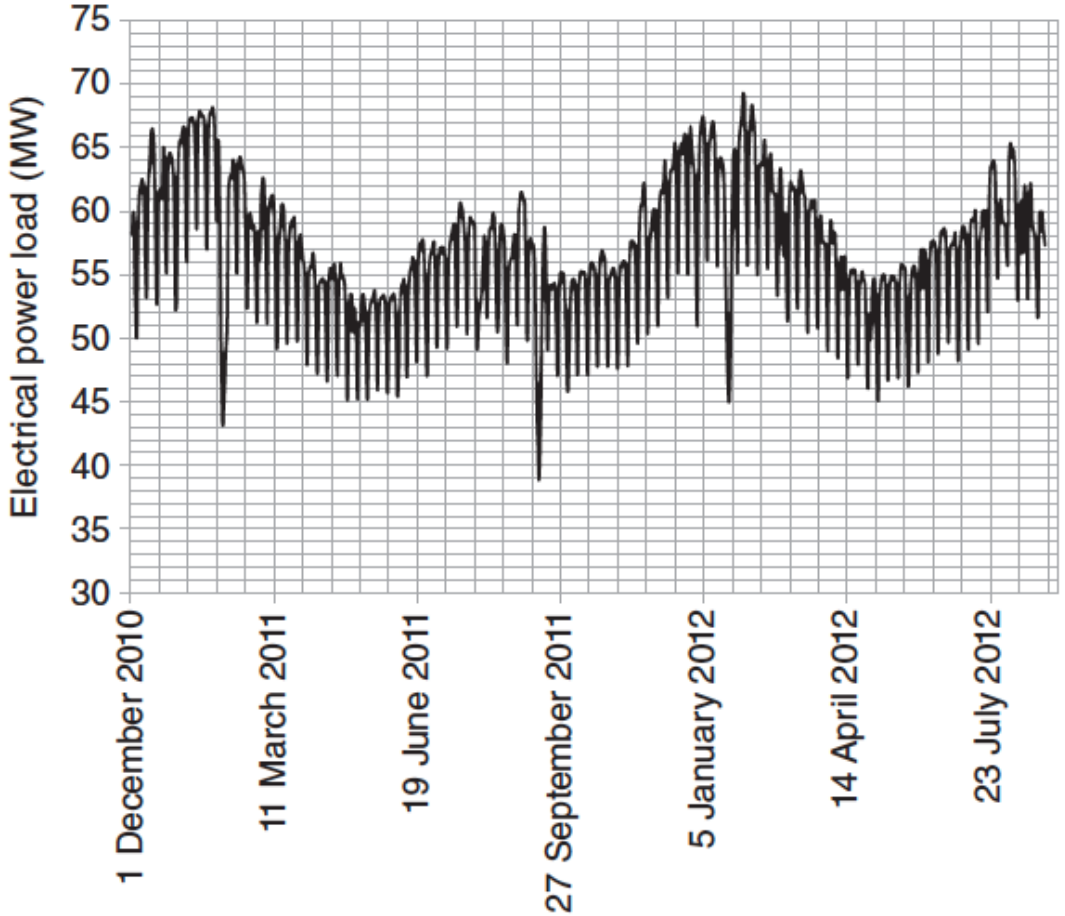
$$= \frac{1}{T} \sum_t e^{i(\Phi_k(t) - \Phi_l(t))}$$

$$R = \begin{pmatrix} 1 & R_{1,2} & \cdots & R_{1,N} \\ R_{1,2}^* & 1 & \cdots & R_{2,N} \\ \vdots & \vdots & \ddots & \vdots \\ R_{1,N}^* & R_{2,N}^* & \cdots & 1 \end{pmatrix}$$

$$R_{k,l||Z} = \frac{\left|R_{kl}^{-1}\right|}{\sqrt{R_{kk}^{-1} R_{ll}^{-1}}}$$

Results: Weather impact on power load





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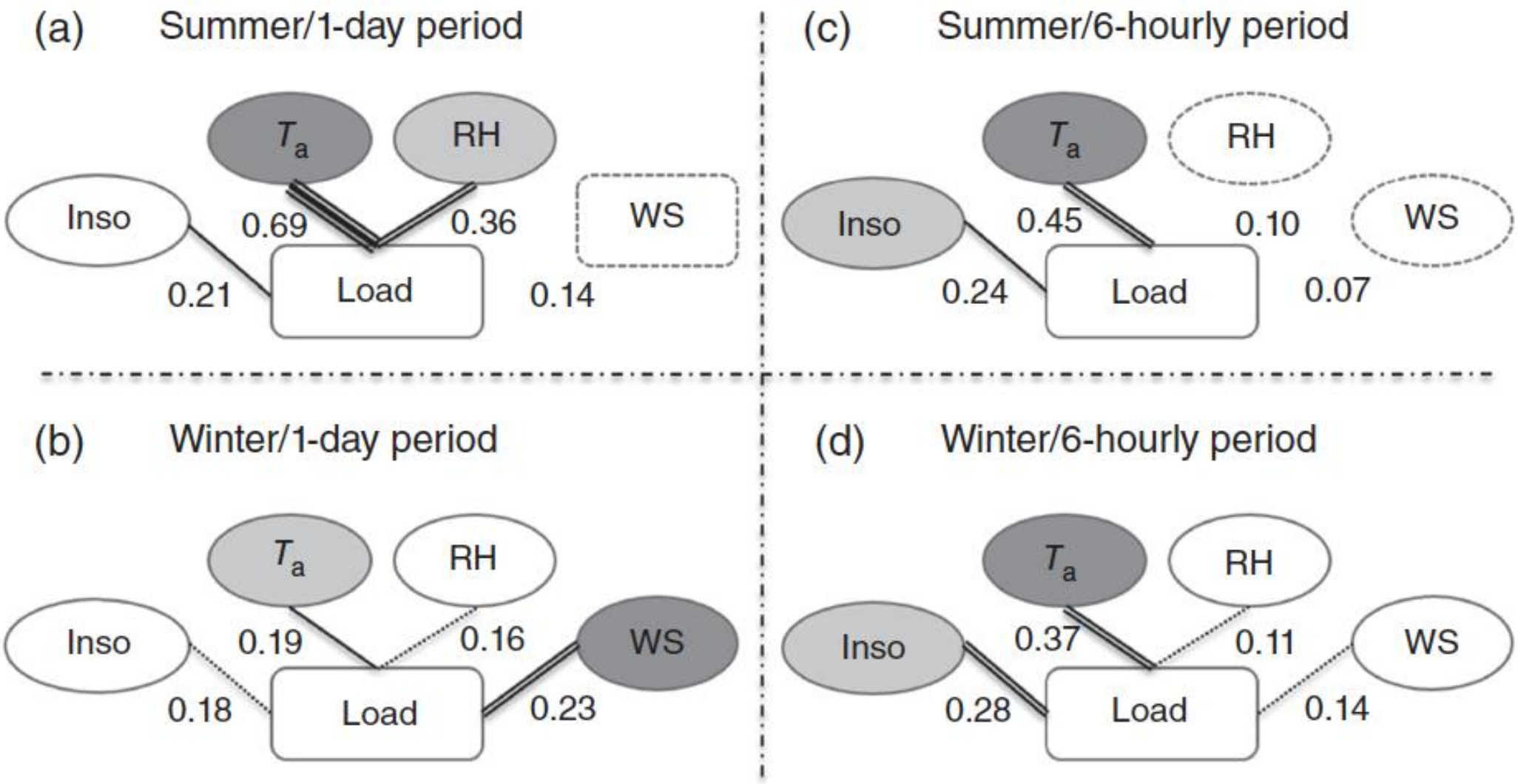

Summary: Weather impact on electricity

✓To proper consider dependencies of covarying meteorological variables, partial phase synchronization index is incorporated with wavelet transform.

✓ Air temperature dependency is significant both in summer and winter but influencing factors show seasonal variation and power forecasting lead time.

- summer: humidity (daily forecasting) / insolation (6-hr forecasting)
- winter: wind (daily forecasting) / insolation (6-hr forecasting)

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- **Electric power load forecasting**
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  - ✓ How can we handle uncertainties in weather forecasting and psychological behaviors in power load forecasting system?

Development of Electric Power Load Forecasting Model

Hybrid fuzzy time series model for power load forecasting

(Lee and Hong, 2015, Int. J. Elec. Pow. & Ener. Syst. / Hong and Lee, 2017, in prep)

Development of Hybrid Power Load Forecasting Model

- **Dynamic model based on air temperature sensitivity**
  - ✓ Dependency of power load on air temperature is significant in short- and mid-term power load forecasting.

- **Development of Fuzzy time series model**
  - ✓ All uncertainties from other weather condition and socioeconomic and psychological factors put in fuzzy time series model.
  - ✓ No weather forecasting data is required: Logical deduction based on autocorrelation of power load time series.

Development of Hybrid Power Load Forecasting Model

Step 1. Partitioning the data into several intervals

Step 2. Generate fuzzy sets and fuzzify the data

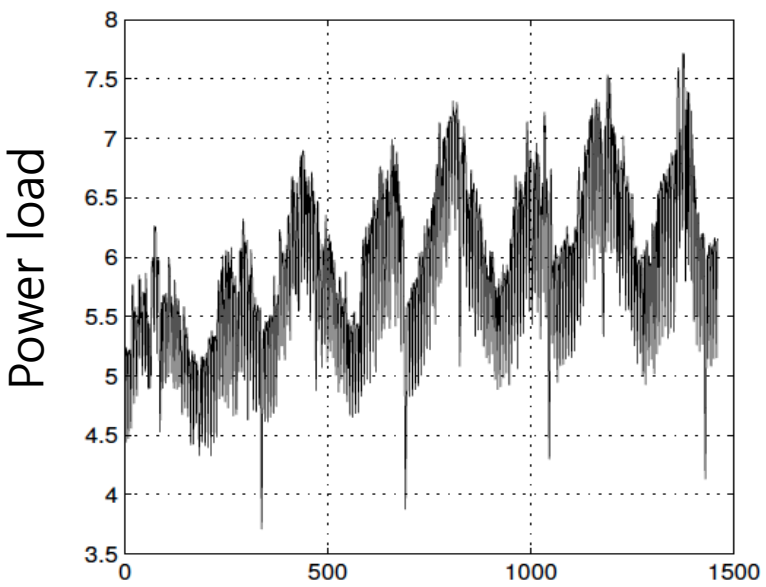
Step 3. Making invariant series and F transformation

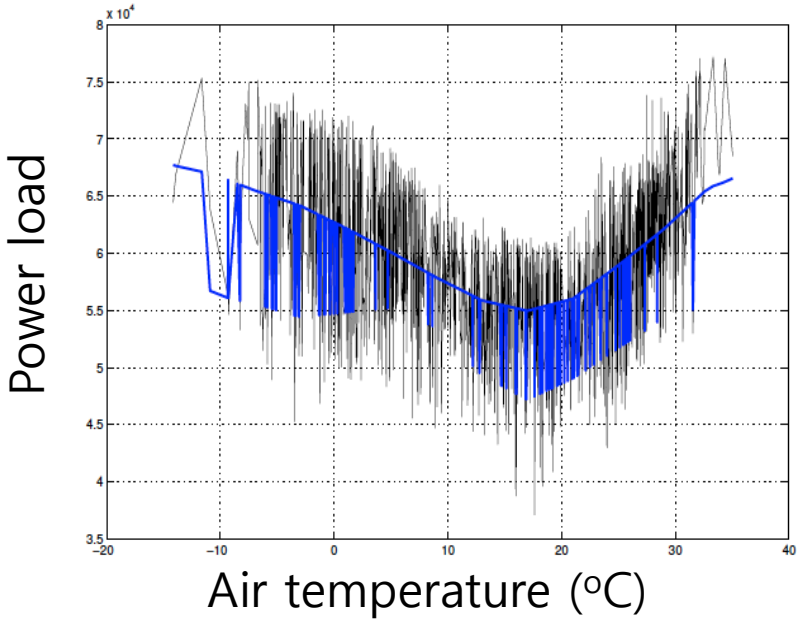
Step 4. Construction of fuzzy logical relationships

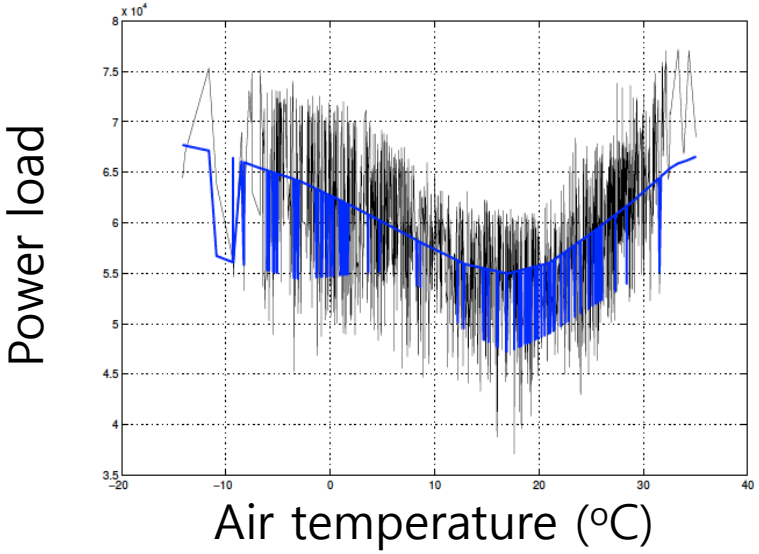
Step 5. Nonfuzzify and calculate the forecasted outputs

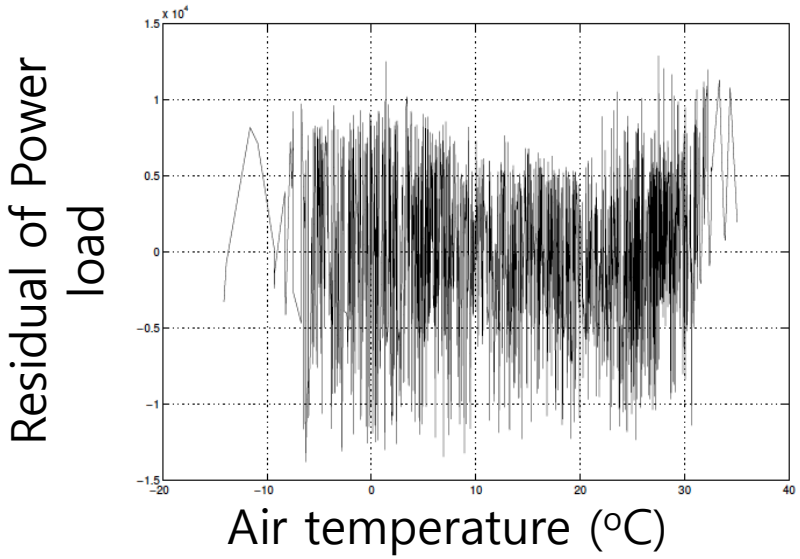
Results: Hybrid model

✓ **Data: 2008.11.01 – 2012.10.31 (4 year data)**



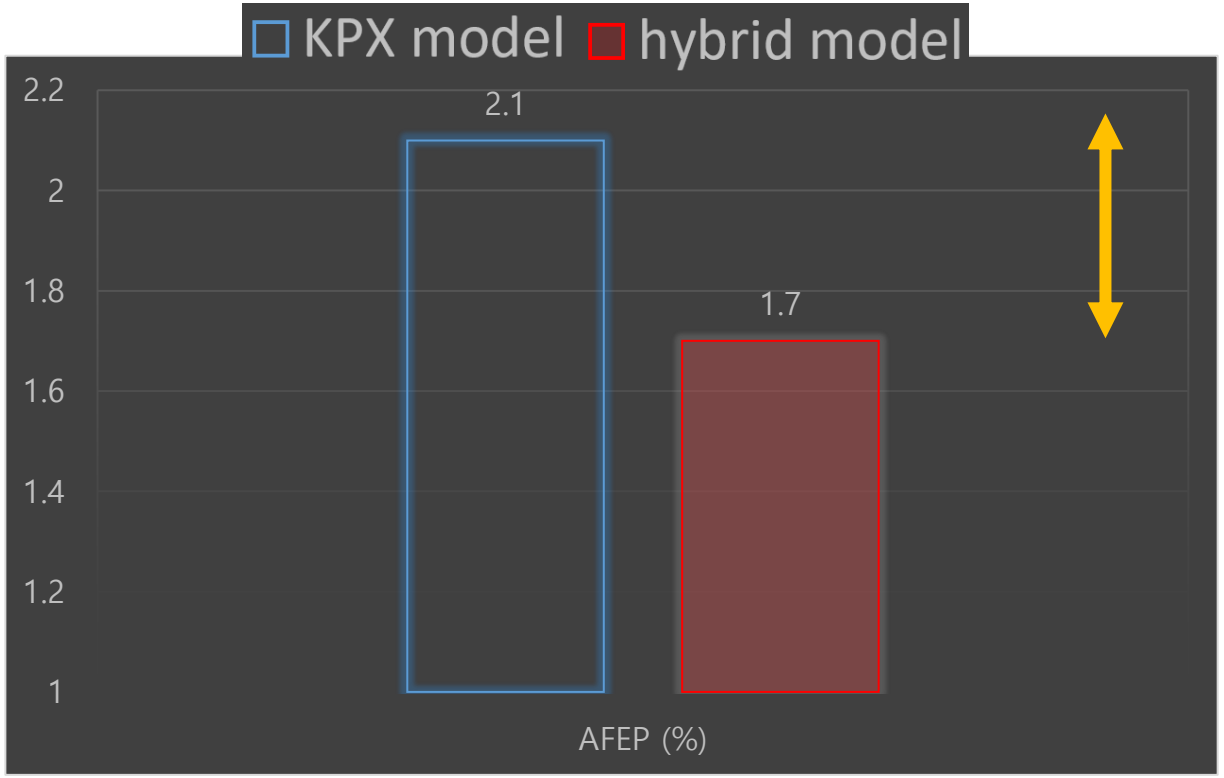






Results: Model Evaluation

✓ **Comparison of the current operational power load forecasting model in KPX**



100 million USD per year

$$\mathrm{AFEP}(\%) = \frac{1}{N}\sum_{i=1}^{N}\left|\frac{P_i - O_i}{O_i}\right| \times 100$$

Note:

1. KPX model is using air temperature forecasting from KMA
2. New hybrid model does not require weather forecasting data

Summary: Hybrid fuzzy power load forecasting model

- ✓To proper consider uncertainties of weather forecasting and other factors new power forecasting model is proposed based on fuzzy time series.
- ✓ Despite non-using of weather forecasting information, the new model produces promising power load forecasting skill compared to the current operational power load forecasting model.

Summary: Hybrid fuzzy power load forecasting model

✓The main advantages of the proposed hybrid model are that

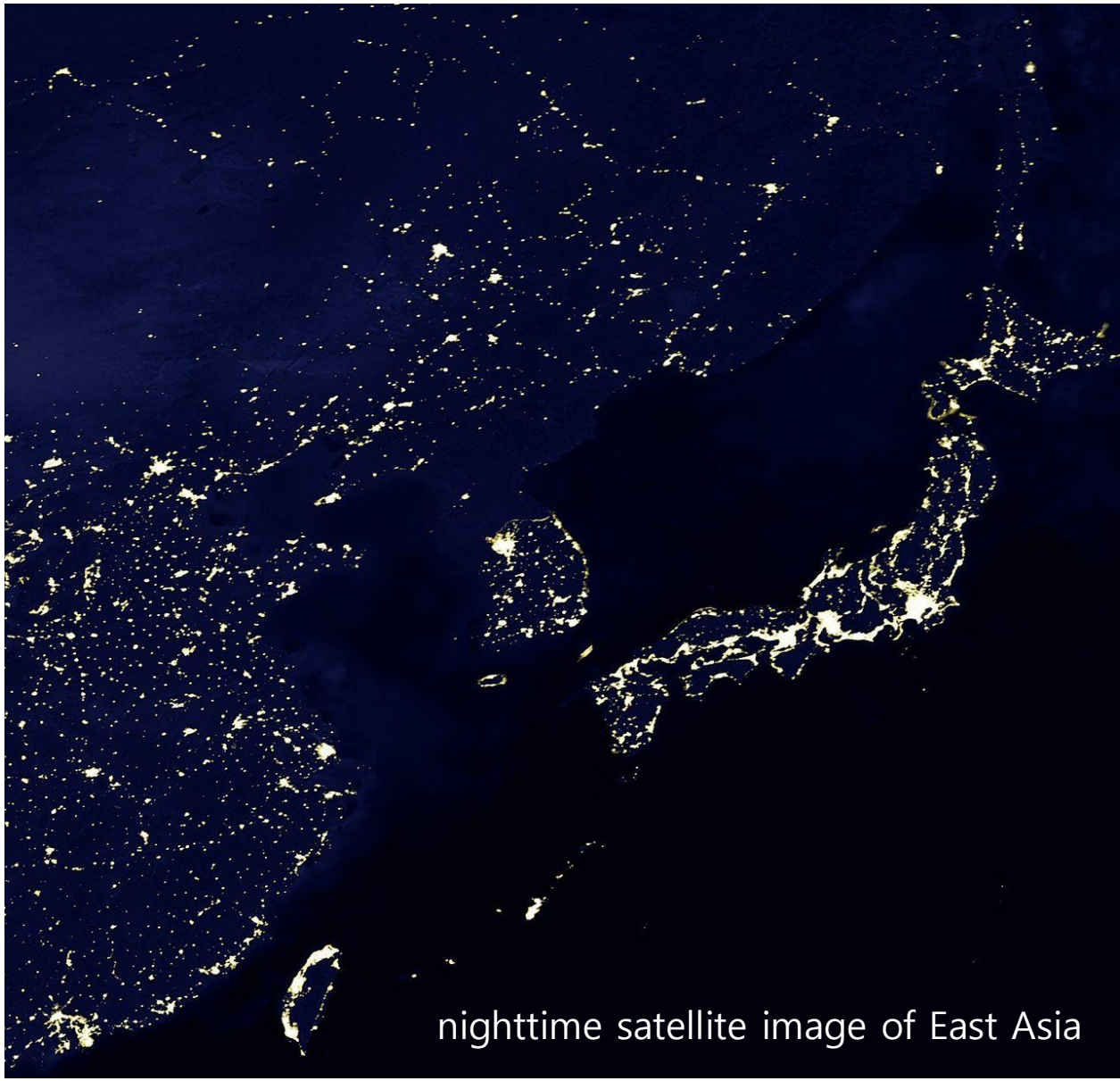
(1) it eliminates the need for the statistical analysis of non-weather factors, and

(2) it can easily be extended to a more complex model by incorporating a multivariate statistical analysis of other independent factors.

Epilogue

- All you need is DATA.

- Traditionally, weather forecasting emphasizes precipitation and new insight on temperature forecasting is in demand.



nighttime satellite image of East Asia


Thank you for your attention
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