Multiple Scenario Forecast for Residential Energy Demands

2015 JST-NSF-DFG-RCN
Workshop on Distributed Energy Management Systems
@Arlington, Virginia, USA

Yu Fujimoto
(Waseda Univ.)

Our Research Team

Project: Development of distributed cooperative EMS methodologies for multiple scenarios by using versatile demonstration platform.

Waseda University

Yasuhiro Hayashi
[Principal Investigator]
- Electric Power Engineering
- Electrical Energy System

Shin-ichi Tanabe
- Architecture
- Building Environmental Engineering

Yoshiharu Amano
- Mechanical Engineering
- Numerical Optimization

Shinji Wakao
- Electric Power Engineering
- Photovoltaic Power Generation System

Noboru Murata
- Information Processing
- Machine Learning

Yu Fujimoto
- Machine Learning
- Data Mining

Shinya Yoshizawa
- Electrical Power Engineering
- Electrical Energy System

…

Osaka University

Yoshiyuki Shimoda
- Environmental Engineering
- Urban Energy System

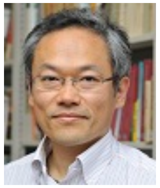
Tokyo Institute of Technology

Hideaki Ishii
- Control System
- Networked Control System

Nagoya University

Shinkichi Inagaki
- Mechatronics

The University of Tokyo



Hiroshi Ohashi
- Economics

…

The University of Tokyo

Junpei Baba
- Power Electronics
- Energy Devices

Hokkaido University

Shin-ichi Minato
- Discrete Structure Manipulation System
- Intelligent Information Processing

Chiba University

Hitoshi Irie
- Remote Sensing
- Atmospheric Environment

Keio University

Hiromitsu Omori
- Control Theory
- Numerical Optimizationgood

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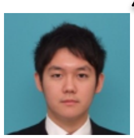

Multiple scenario forecast for residential energy demands

(Joint work with professor Murata)

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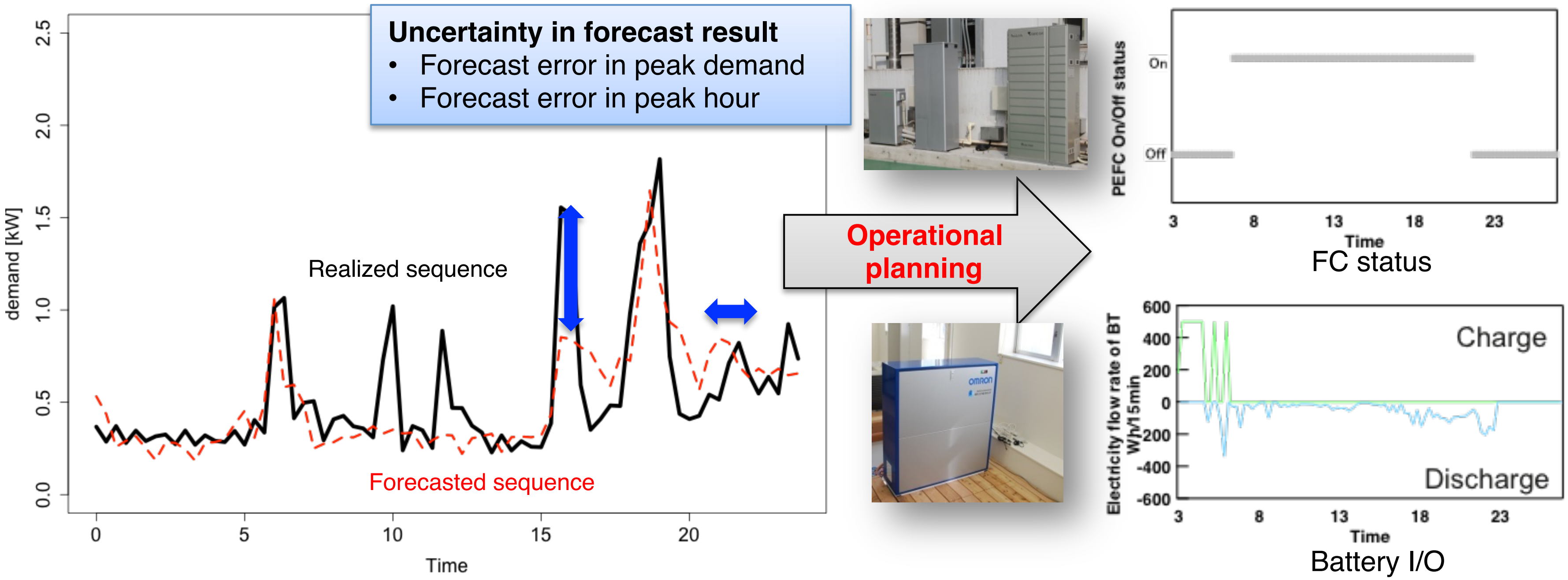
Residential demand forecast is necessary for :

- Determining operational planning of residential energy appliances (from HEM perspective)
- Determining operation parameter of voltage controllers (from GEM perspective)
- …

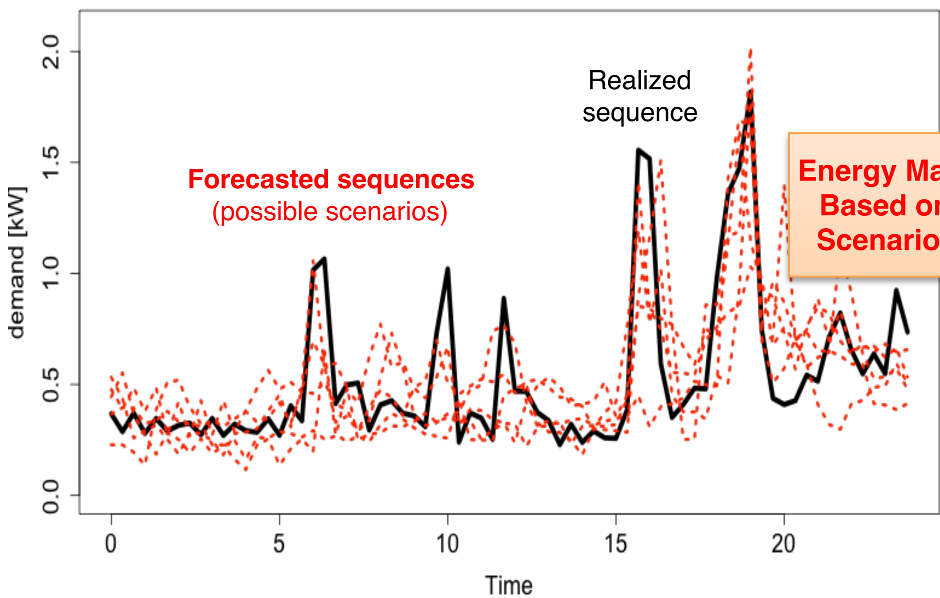


Schematic image of demand forecast for operational planning of residential energy appliances

- Forecast error causes inefficient operational planning for energy appliances.
- <u>We have to handle uncertainty in forecast</u> for optimal planning.

Multiple scenario forecast

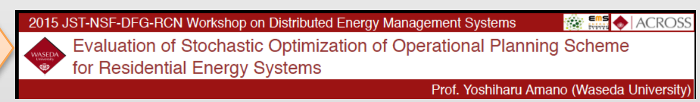
- Handling uncertainty in forecast by providing several *plausible* future demand curves under current condition (context).
- Suitable for :
  - ➢ Scenario-based stochastic optimization in operational planning of residential energy appliances
  - ➢ Robust parameter determination of voltage controllers on distribution networks
  - ➢ …



An example of multiple scenario forecast

Energy Management Based on Multiple Scenario Forecast

Several utilization results were already presented from our team in yesterday's poster session.



2015 JST-NSF-DFG-RCN Workshop on Distributed Energy Management Systems

Evaluation of Stochastic Optimization of Operational Planning Scheme for Residential Energy Systems

Prof. Yoshiharu Amano (Waseda University)

Professor Amano

2015 JST-NSF-DFG-RCN Workshop on Distributed Energy Management Systems

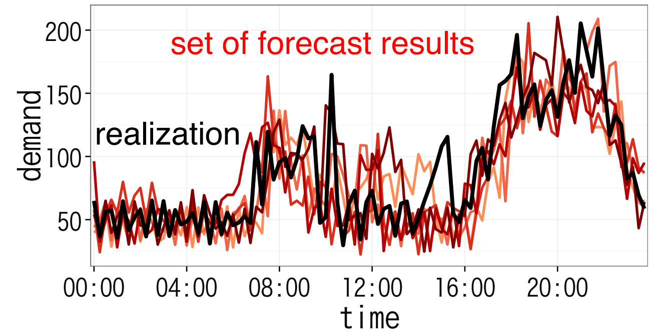
Determination Method of Voltage Control Parameters Based on Input-output Relationship Database in Distribution System

Shinya Yoshizawa (Waseda University)

PhD student Yoshizawa

Basic idea

- Extracting *plausible* load curves (*outputs*) under *similar* contexts (*inputs*) from the database according to the K-nearest neighbor (K-NN) framework.



Multiple Scenario forecast

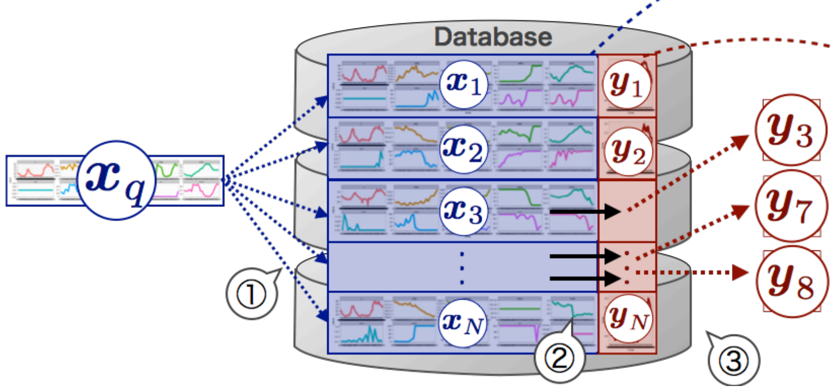
K-NNs enables us to obtain **multiple candidates** of y_q by selecting neighbors $\mathcal{N}_q^{\mathcal{X}}$ of x_n from database which stores $\{x_n, y_i\}_{i=1}^{N}$.

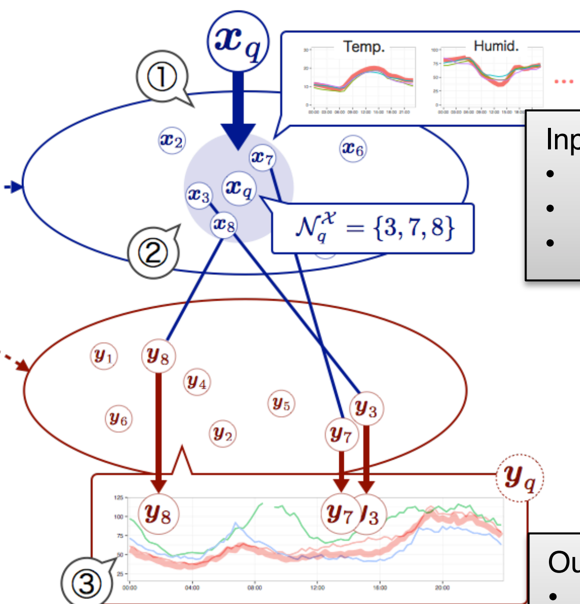
Prediction procedure

① Input x_q to DB, and select neighbors $\mathcal{N}_q^{\mathcal{X}}$.

② Relate to counterparts y_n, $i \in \mathcal{N}_q^{\mathcal{X}}$.

③ Output $\{y_n\}_{n \in \mathcal{N}_q^{\mathcal{X}}}$ as prediction candidates.





Input (current context)
- Load curves of last *N* days
- Weather forecast results
- …

Output (forecasted results)
- A set of daily load curves
  - ➢ Energy load
  - ➢ Thermal load

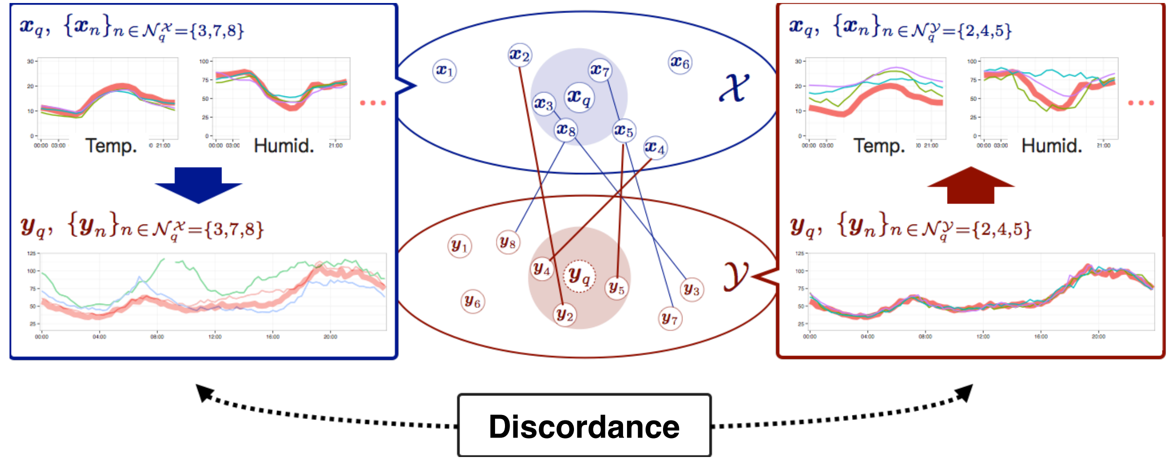
Schematic image of load forecast based on K-Nearest Neighbor JIT (Just-In-Time) modeling

Providing plausible future load curves

- Extracting a set of outputs caused under similar contexts.
  - ➢ How should we define appropriate similarity between contexts?

Problem in K-NN based forecast approach

- Discordance between K-NNs in input data space and those in output data space.
  - ➢ K-NNs of current context do NOT indicate K-NNs of the actual realization.

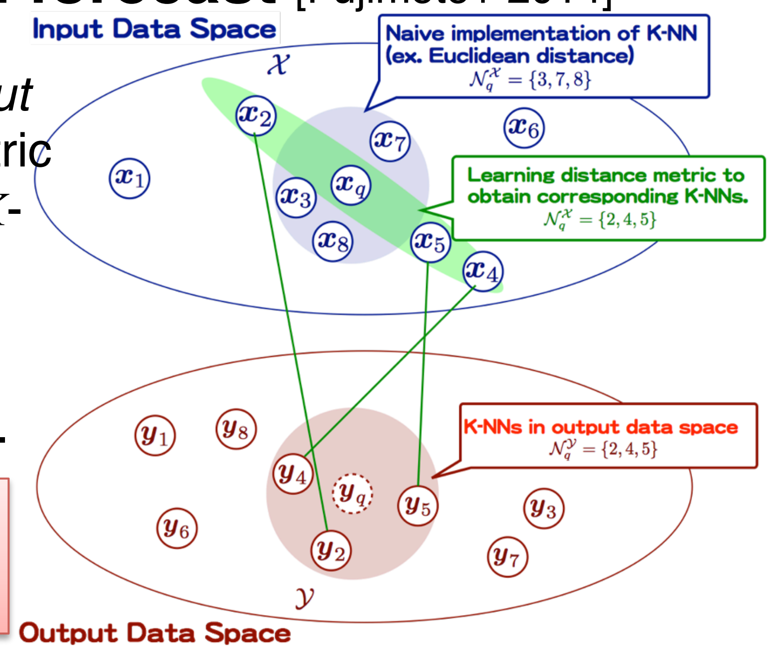


Distance metric learning for K-NN forecast [Fujimoto+ 2014]

- *Learning appropriate distance metric in input data space* by using the given distance metric in output data space to obtain concordant K-NNs.

- Focusing on a class of generalized Mahalanobis distance between two vectors.

Appropriate distance metric for measuring input sequences can be derived according to ordinary least square framework by only using simple linear algebra.



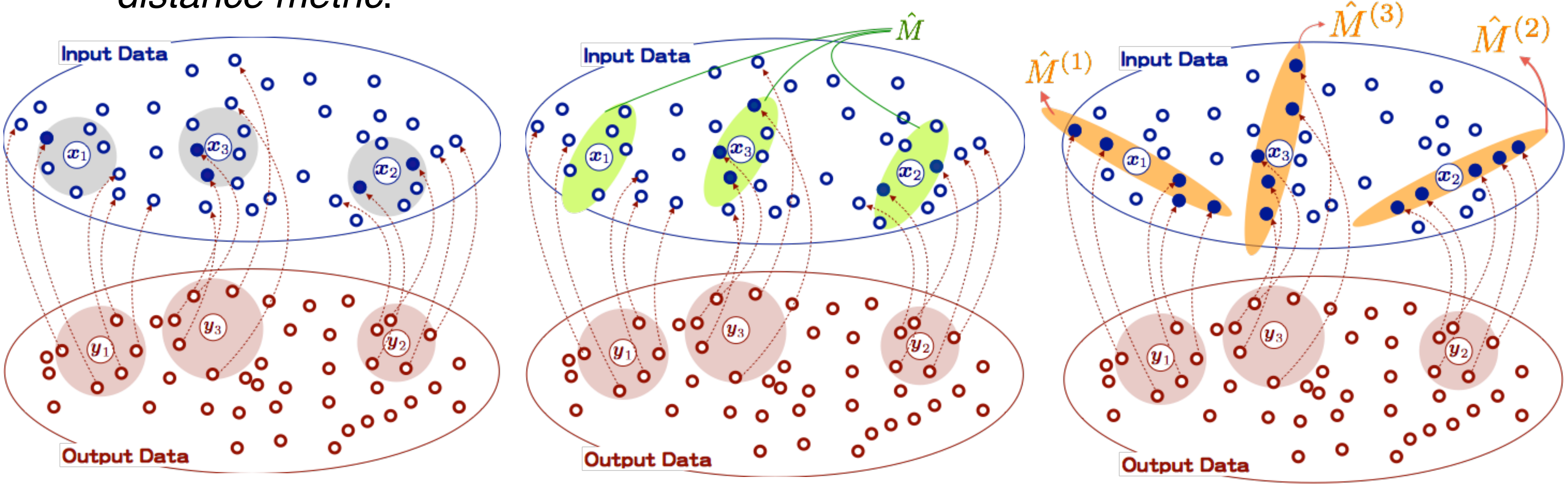
Local distance metric learning for multiple scenario forecast:

[Fujimoto+2014]

- Providing flexible and appropriate distance metric for each input.
- Improving discordance between K-NNs in input data space and those in output data space.
- Providing context-oriented plausible multiple scenario forecast *based on context-oriented distance metric*.

Algorithm 1 Local Distance Metric Learning

Input: n, $\mathcal{D}$, $d^{\mathcal{Y}}$, K, $I_{\max}$.
  $\boldsymbol{M}_n^{(0)} \leftarrow \boldsymbol{I}$.
  for $i = 0$ to $I_{\max}$ **do**
    $K_L^{(i)} \leftarrow \left| \left\{ l \in \{1, \ldots, N\}; d_{nl}^{\mathcal{X}}(\boldsymbol{M}_n^{(i)}) \leq \max_{m \in \mathcal{N}_n^{\mathcal{Y}}} d_{nm}^{\mathcal{X}}(\boldsymbol{M}_n^{(i)}) \right\} \right|$.
    $\mathcal{D}_n \leftarrow \{(\boldsymbol{x}_m, \boldsymbol{y}_m); m \in \mathcal{N}^{\mathcal{X}}(\boldsymbol{x}_n; K_L^{(i)}, d^{\mathcal{X}}(\boldsymbol{M}_n^{(i)}))\}$.
    Estimate $\boldsymbol{M}_n^{(i+1)}$ by using $\mathcal{D}_n$ based on RML.
  end for
  $\hat{i} \leftarrow \mathrm{argmin}_{i \in \{0, \ldots, I\}} K_L^{(i)}$.
  $\boldsymbol{M}_n \leftarrow \boldsymbol{M}_n^{(\hat{i})}$.
Output: $\boldsymbol{M}_n$

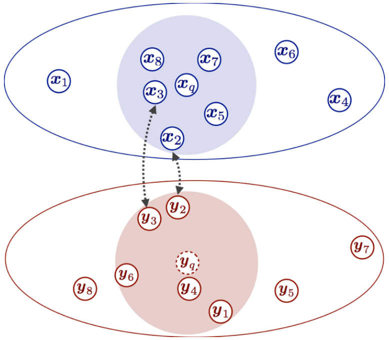


Naïve K-NN implementation based on Euclidean distance

Global metric learning for K-NN forecast

Local metric learning for K-NN forecast

Purpose:



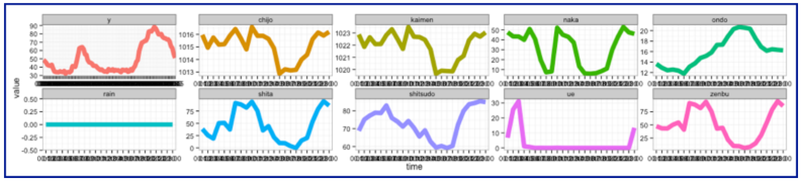
- Evaluation of appropriateness of proposed forecast scheme from the view point of selection accuracy of the K-NNs
  - ➢ Cardinality of intersection between K-NNs in input and output spaces.

Simpson coefficient $$SC_q = \frac{|\mathcal{N}_q^{\mathcal{X}} \cap \mathcal{N}_q^{\mathcal{Y}}|}{\min(|\mathcal{N}_q^{\mathcal{X}}|, |\mathcal{N}_q^{\mathcal{Y}}|)},$$

- Comparing the following multiple scenario forecast frameworks:
  - ➢ Naïve K-NN implementation based on the Euclidean distance (**EUC**)
  - ➢ K-NN based on the regression based global distance metric learning (**RML**)
  - ➢ K-NN based on the regression based local distance metric learning (**RLML**)

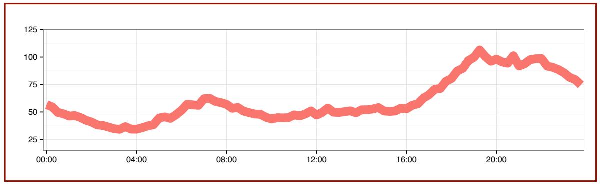
Experimental setup:

- Input
  - ➢ Load curve of previous day (15min., 96-dim.)
  - ➢ Weather forecast of next day (1hour, 24-dim. 9vars).
    - ✓ Temperature, humidity, …



An example of input query (current context)

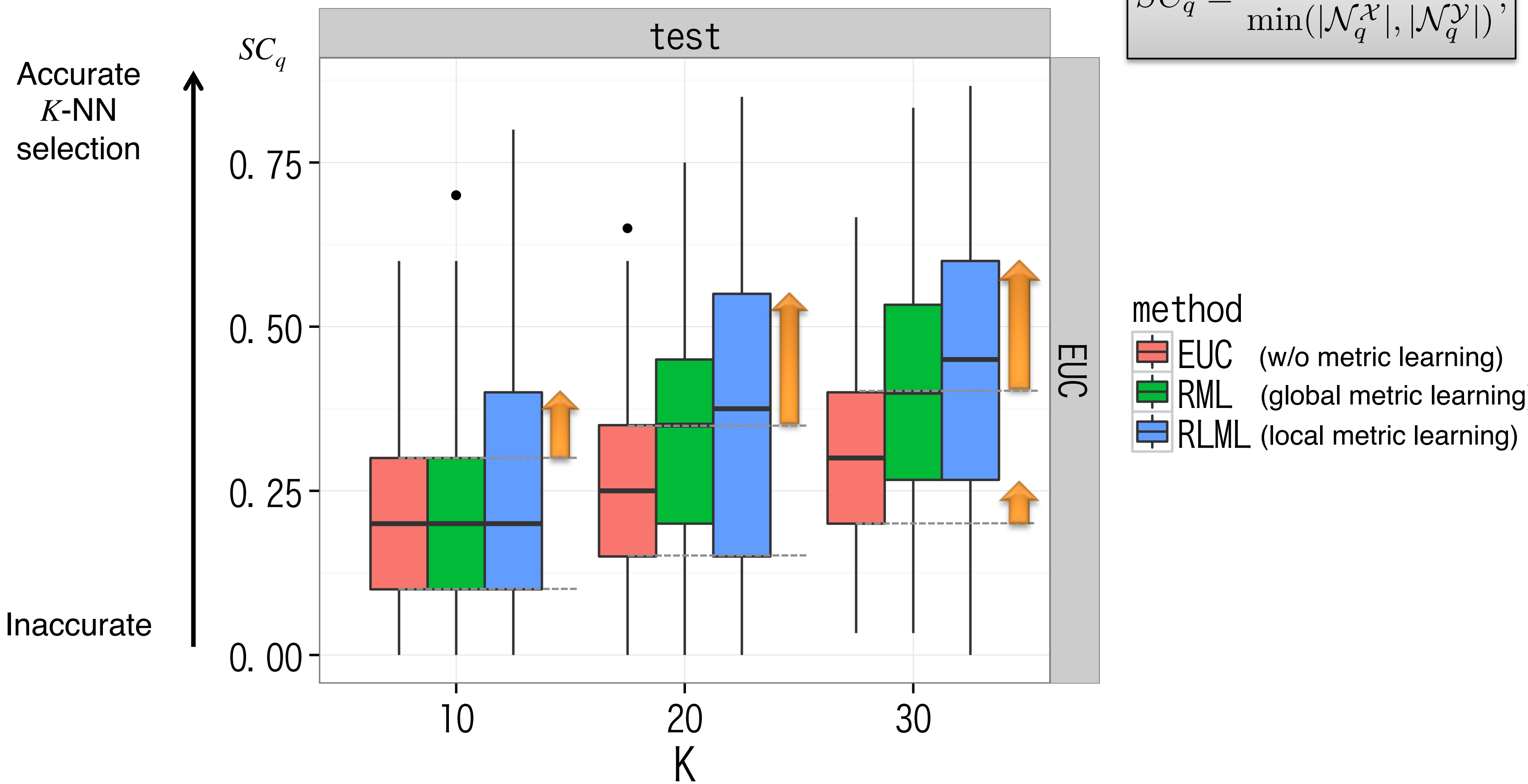
- Output
  - ➢ Load curve of next day (15min., 96-dim.)
- Other setups
  - ➢ Number of samples: 450 days of input-output pairs in DB.
  - ➢ K: 10, 20, 30
  - ➢ Distance metric <u>for output space</u>: Euclidean distance.
  - ➢ Targeted load: total load of 550 houses



An example of output target (realization)

Simpson coefficients

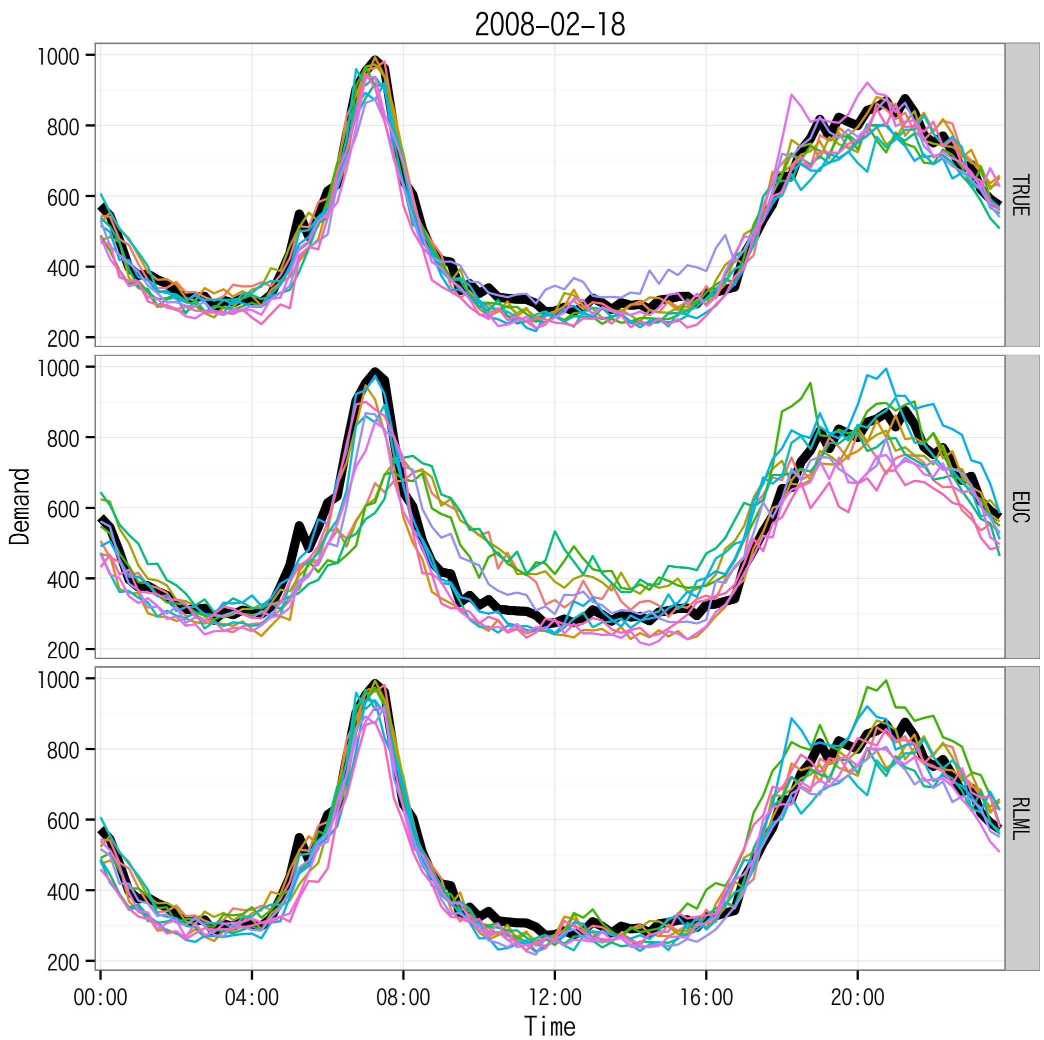
$$SC_q = \frac{|\mathcal{N}_q^{\mathcal{X}} \cap \mathcal{N}_q^{\mathcal{Y}}|}{\min(|\mathcal{N}_q^{\mathcal{X}}|, |\mathcal{N}_q^{\mathcal{Y}}|)},$$



Results of Simpson coefficients

- Our proposed framework improves accuracy in selection of the actual K-NNs of the realizations under various K by using distance metric learning.
- Local distance metric learning improves selection accuracy.

A Result of Multiple Scenario Forecast



K-NNs in output space
- Ideal scenarios

Simpson coefficient: 1.0

Conventional naïve approach
- Forecasted scenarios w/o metric learning [**EUC**]

Simpson coefficient: 0.1

Proposed approach
- Forecasted scenarios based on local metric learning [**RLML**]

Simpson coefficient: 0.8

- Forecasted load curves based on our method adequately represent the plausible candidates which can occur under current context.

We proposed a multiple scenario demand forecast framework.

- Providing multiple load curves for representing uncertainty.
- Selecting plausible candidates based on the learned distance metric.
- Improving <u>forecast accuracy</u> based on the local metric learning.

Accurate forecast for what?

- We evaluated our method only in terms of forecasting accuracy.
  - ➢ The appropriateness and the impact of forecasting uncertainty <u>should be evaluated in the context of energy management.</u>

- Effectiveness of our approach is being verified from the viewpoint of the EMS.

Thank you for your attention

Vielen Dank für Ihre Aufmerksamkeit

Takk for din oppmerksomhet

ご清聴ありがとうございました