Electric Demand Prediction and Predictive Control of Micro Grid

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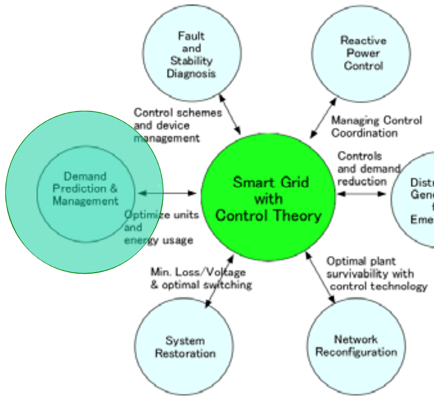
PACIFICO YOKOHAMA

Networked Smart Grid with Control Theory



Introduction

- Power generation scheduling plays a key role for an economical operation and a low CO2 emission.
- Short-time electrical power demand prediction, 36 hour prediction (Tomorrow's operation scheduling)

- Past Time history of electrical demand
- Weekday/weekend /holiday information
- Season
- Temperature

Electrical Power Demand Prediction → **Tommorow's Power Generation Scheduling** → **Operation on the Day**

Problem Formulation

- Electrical Demand Model
  - Demand at one hour before
  - Demand at 24 hours before
  - Temperature

$$\begin{aligned} y(k) = & \; a_0(k) + a_1(k)y(k-1) + a_{23}(k)y(k-23) \\ & + a_{24}(k)y(k-24) + a_{25}(k)y(k-25) \\ & + b_0(k)t(k) + b_1(k)t(k-1) + b_{24}(k)t(k-24) \end{aligned} \quad (1)$$

k: Time [h]
$y(k)$: Demand [MW] $a_0(k), \cdots, a_{25}(k)$: Constant (Unknown)
$t(k)$: Temp [deg] $b_0(k), b_1(k), b_{24}(k)$: Constant (Unknown)
$y(k-i), t(k-i)$ Data i hour before at time k

Parameter Estimation via $\mathcal{H}_\infty$ Filter

- Electrical Demand Model

$$\begin{aligned} y(k) = & \; a_0(k) + a_1(k)y(k-1) + a_{23}(k)y(k-23) \\ & + a_{24}(k)y(k-24) + a_{25}(k)y(k-25) \\ & + b_0(k)t(k) + b_1(k)t(k-1) + b_{24}(k)t(k-24) \end{aligned} \quad (1)$$

- Discrete-Time State Space Representation

$$x(k+1) = x(k) \quad (2)$$

$$z(k) = C(k)x(k) + v(k) \quad (3)$$

Estimation Parameters: $x(k) = [a_0 \;\; a_1 \;\; a_{23} \;\; a_{24} \;\; a_{25} \;\; b_0 \;\; b_1 \;\; b_{24}]^T$
Past data for Learning: $C(k) = [1 \;\; y(k-1) \;\; y(k-23) \;\; y(k-24) \;\; y(k-25) \;\; t(k) \;\; t(k-1) \;\; t(k-24)]$

Parameter Estimation via $\mathcal{H}_\infty$ Filter

- State Estimation Problem

For a given $\gamma > 0$, find a filter which achieves

$$\sup_{x_0, v} \frac{\sum_{k=0}^{N} \|x(k) - \hat{x}(k)\|^2}{\|x(0) - \hat{x}(0)\|^2_{P(0)^{-1}} + \sum_{k=0}^{N} \|v(k)\|^2_{R^{-1}}} < \gamma^2 \quad (4)$$

- $\mathcal{H}_\infty$ filter

$$\begin{aligned} K(k) &= P(k)C(k)^T\left(C(k)P(k)C(k)^T + R\right)^{-1} && (5) \\ \hat{x}(k+1) &= \hat{x}(k) + K(k)\left(z(k) - C(k)\hat{x}(k)\right) && (6) \\ P(k+1) &= \left(P(k)^{-1} + C(k)^T R^{-1} C(k) - \gamma^{-2} I\right)^{-1} && (7) \end{aligned}$$

- Consensus Filter

H. Kawakami and Toru Namerikawa, "Consensus Filter Based Target-enclosing Strategies for Multiple Nonholonomic Vehicles," *IEEE CDC*, 2008.

Electric Demand Prediction

- Sequence of Demand Prediction $\hat{y}$
- Prediction of One Hour Future

$$
\begin{aligned}
\hat{y}(k+1) = {} & a_0(k) + a_1(k)y(k) + a_{23}(k)y(k-22) \\
& + a_{24}(k)y(k-23) + a_{25}(k)y(k-24) \\
& + b_0(k)t(k+1) + b_1(k)t(k) + b_{24}(k)t(k-23) \qquad (8)
\end{aligned}
$$

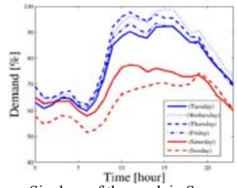
$\vdots$

Prediction based on Predicted Value

- Prediction of 36 Hour Future

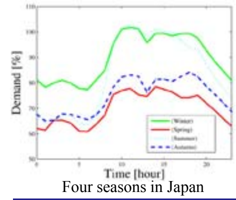
$$
\begin{aligned}
\hat{y}(k+36) = {} & a_0(k) + a_1(k)\boxed{\hat{y}(k+35)} + a_{23}(k)\boxed{\hat{y}(k+13)} \\
& + a_{24}(k)\boxed{\hat{y}(k+12)} + a_{25}(k)\boxed{\hat{y}(k+11)} \\
& + b_0(k)t(k+36) + b_1(k)t(k+35) + b_{24}(k)t(k+12) \qquad (9)
\end{aligned}
$$

Demand Curve Properties and Variations



Six days of the week in Summer

- Weekday(WD)
  - Bigger Change in a Day
  - High Peak Demand
- Weekend(WE)
- Holiday(HD)
  - Smaller Change
  - Low Peak
- **WD** and **WEHD** Model



Four seasons in Japan

- Summer
- Winter
  - Bigger Change in a Day
  - High Peak Demand
- Spring
- Autumn
  - Smaller Change
  - Low Peak
- Four Models for each season

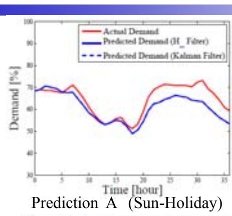
Numerical Simulation : Scenario

- Load and temperature in 2004 – 2008
- Future temp is assumed to be correct
- Target period includes holidays
- Past 30 days information is utilized for Parameter Estimation

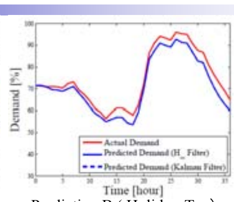
	Filtering	Load Prediction
Case 1	Kalman F. and H_inf Filter	WD & WEHD
Case 2	H_inf Filter	Conventional and WD & WEHD

SUN	MON	TUE	WED	THU	FRI	SAT
1	2	3	4	5	6	7
8	9	10	11	12	13	14
Prediction A	Holiday	Prediction B				
15	16	17	18	19	20	21
	Prediction C	Holiday	Prediction D			

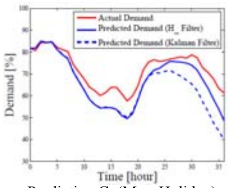
Simulation Results : Case 1



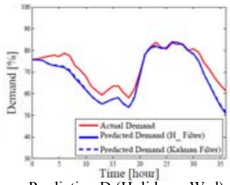
Prediction A (Sun-Holiday)



Prediction B (Holiday-Tue)



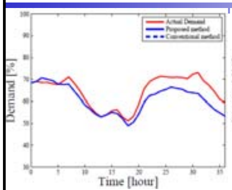
Prediction C (Mon-Holiday)



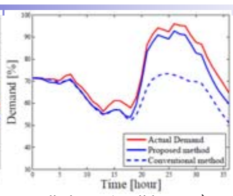
Prediction D (Holiday – Wed)

- Prediction C shows remarkable improvement
- There have been some improvements in relatively future time

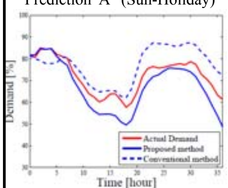
Simulation Results : Case 2



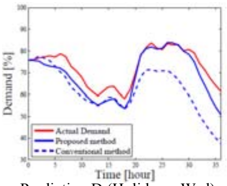
Prediction A (Sun-Holiday)



Prediction B (Holiday-Tue)



Prediction C (Mon-Holiday)



Prediction D (Holiday – Wed)

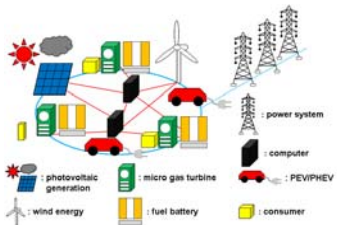
- Decoupling betw. weekday and WE/HD makes remarkable performance improvement

Predictive Control of Micro Grid

- **Micro Grid**
- Large Scale Power System
- Distributed and Complex

By using control technology

- save energy
- reduce cost
- increase reliability and transparency



Micro Grid

- Supply of renewable energy is unstable (predictable over finite future)
- Demand varies with time and season (predictable over finite future)
- Artificial power generation and capacity of battery are limited

Goal of this Research

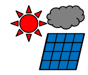
To present a framework of **predictive control** to operate energy network system successfully

Decentralized/ Distributed and Predictive Control Structure
to determine the optimal (controllable) MGT power generation while satisfying system constraints

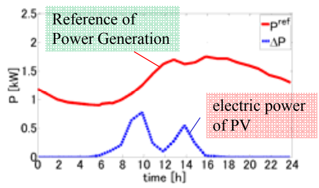
Control Problem for Systems which consist of multiple subsystems collecting Spatiotemporally different information.

PV, Micro Gas Turbine and Strage

- **Design of Micro Grid**
  - Photovoltaics(PV)

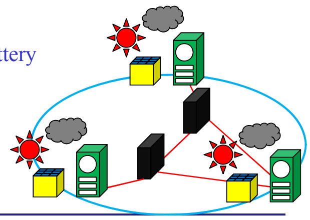


Prediction of Power Generation
by Weather News



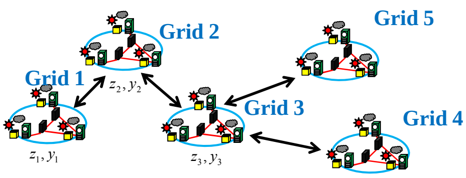
  - Micro gas turbine(MGT)/Battery
    (controllable)

Control Input



System Description

- **Linear Time Invariant Distributed Systems**



$$x_i(t+1) = \sum_{j=1}^{N} A_{ij} x_j(t) + B_i u_i(t) + F_i w_i(t)$$

$x_i(t) \in R^{n_x}$: State $\quad t \in Z_+$
$u_i(t) \in R^{n_u}$: control input
$w_i(t) \in R^{n_w}$: zero mean white process and sensor noises

System Description

- **Linear Time Invariant System with Information Structure**

$$x(t+1) = Ax(t) + Bu(t) + Fw(t) \qquad (1)$$
$$y(t) = Cx(t) + v(t)$$

$x(t) \in R^{n_x}$: State $\quad t \in Z_+$
$u(t) \in R^{n_u}$: control input $\quad y(t) \in R^{n_y}$: control measurement
$w(t) \in R^{n_w}$ $\quad v(t) \in R^{n_v}$: zero mean white process and sensor noises

System (1) is controllable and observable, and satisfies

$$\mathbf{E}\begin{bmatrix} w(t) \\ v(t) \end{bmatrix}\begin{bmatrix} w^T(s) & v^T(s) \end{bmatrix} = \begin{bmatrix} R_{ww} & 0 \\ 0 & R_{vv} \end{bmatrix}\delta_{ts} \qquad (2)$$
$$\delta_{ts} = 1 \text{ if } t = s \qquad \delta_{ts} = 0 \text{ if } t \neq s$$

$$\mathbf{E}w(t)x^T(s) = 0 \qquad \mathbf{E}v(t)x^T(s) = 0 \quad \text{if} \quad t \geq s \qquad (3)$$

Information Structures

The information structures can be modeled
by using the covariance constraints for general systems.

- Covariance Constraints

$$\mathbf{E}\, u_i(t) w_j^T(t-\tau) = 0 \quad \text{if} \quad \tau \leq \mathrm{dist}(\, i\, ,\, j) \qquad (6)$$

where $\tau \in Z_+$

$\mathrm{dist}(\, i\, ,\, j)$ is a distance between subsystem i and j

A. Rantzer, ``A Separation Principle for Distributed Control,''
Proc. of the 45th IEEE CDC, 2006

Covariance Constraints

- State Estimation

$$\mathbf{E}\, y_i(t) v_j^T(t-\tau) = 0 \quad \text{if} \quad \tau \leq \mathrm{dist}(\, i\, ,\, j)\text{-}1 \qquad (7)$$

- Power Constraints

$$\mathbf{E}\, x^T(t) Q_x x(t) + u^T(t) Q_u u(t) \leq \gamma \qquad Q_x, Q_u > 0 \qquad (8)$$

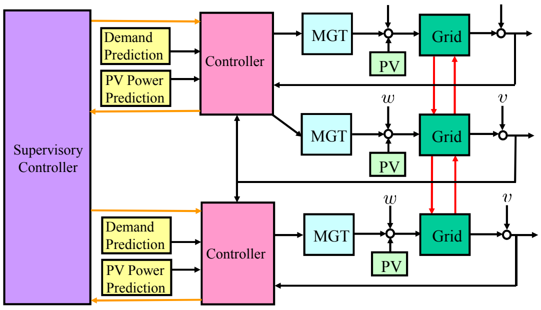
- Mean polytopic constraints for state and input

$$\mathbf{E}\begin{bmatrix} x(t) \\ u(t) \end{bmatrix} \in D \subset R^{n_x + n_u} \qquad (9)$$

where D is a convex polytope including the origin as an interior.

Structure of Control System

We present a decentralized predictive control structure to determine the optimal (controllable) MGT power generation while satisfying system constraints



Predictive Control Law

- **Constrained Finite-Time Optimal Control problem**

  State feedback predictive control law i.e. $C = I$ *and* $v \equiv 0$ *for systems with information structures* like micro grid

- **Problem 1**

$$\min_{u(0),\dots,u(N_C-1)} \mathbf{E}\left\{ x^T(N_C) P_{N_C} x(N_C) + \sum_{j=0}^{N_C-1} \begin{bmatrix} x(j) \\ u(j) \end{bmatrix}^T P \begin{bmatrix} x(j) \\ u(j) \end{bmatrix} \right\}$$

subject to

$$x(t+1) = Ax(t) + Bu(t) + Fw(t) \qquad x(0) = y_0 + v(0)$$

$$\mathbf{E}\begin{bmatrix} x(k) \\ u(k) \end{bmatrix}^T Q_r \begin{bmatrix} x(k) \\ u(k) \end{bmatrix} = 0 \qquad \mathbf{E}\begin{bmatrix} x(k) \\ u(k) \end{bmatrix}^T Q \begin{bmatrix} x(k) \\ u(k) \end{bmatrix} < \gamma \qquad Q = \begin{bmatrix} Q_x & 0 \\ 0 & Q_y \end{bmatrix}$$

$$r = 1, 2, \dots, m$$

$$\mathbf{E}\begin{bmatrix} x(t) \\ u(t) \end{bmatrix} \in D \subset R^{n_x + n_u} \qquad \mathbf{E}x(N_C) \in F$$

Terminal constraint set

Main Result

Theorem 1 Problem 1 is reduced to the following **deterministic optimization problem**, **Problem 2**

- **Problem 2**

$$\min_{s,\lambda} s \text{ subject to } \begin{bmatrix} \overline{\Phi}(\lambda) & \widetilde{\Psi} \\ * & \widetilde{\eta}(\lambda) + s \end{bmatrix} > 0$$

$$\overline{\Phi}(\lambda) := \Phi + \sum_{l=1}^{M} \lambda_l Q_l^u \qquad \widetilde{\Psi} := (\Psi + \sum_{l=0}^{M} \sum_{l=1}^{M} \lambda_l Q_l^{ux}) \begin{bmatrix} x(0) \\ W(0) \end{bmatrix}^T + \sum_{l=M+1}^{M+N} \lambda_l A_l^u$$

$$\widetilde{\eta}(\lambda) := \begin{bmatrix} x(0) \\ W(0) \end{bmatrix}^T \overline{\Gamma}(\lambda) \begin{bmatrix} x(0) \\ W(0) \end{bmatrix} - \sum_{l=1}^{M} \lambda_l \gamma_l + \sum_{l=M+1}^{M+N} \lambda_l A_l^u \left(\begin{bmatrix} x(0) \\ W(0) \end{bmatrix} - b_l \right)$$

$$\overline{\Gamma}(\lambda) := \Gamma + \sum_{l=1}^{M} \lambda_l Q_l^x$$

Another Result : Distributed Estimation

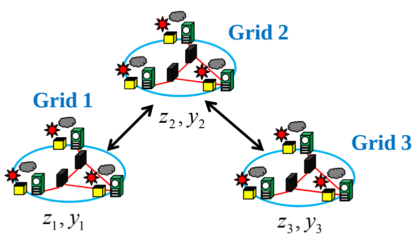
- Employ a moving horizon estimator with variance minimization for state estimation in order to get a state estimate.

- The objective function to be minimized is given by

$$\mathbf{E}\sum_{i=0}^{N_C} \left(y(t-i) - C\hat{x}(t-i) \right)^T Q_e \left(y(t-i) - C\hat{x}(t-i) \right)$$

- Using the same procedure, the above minimization problem under the communication delay constraint (7) is also reduced to an LMI problem.

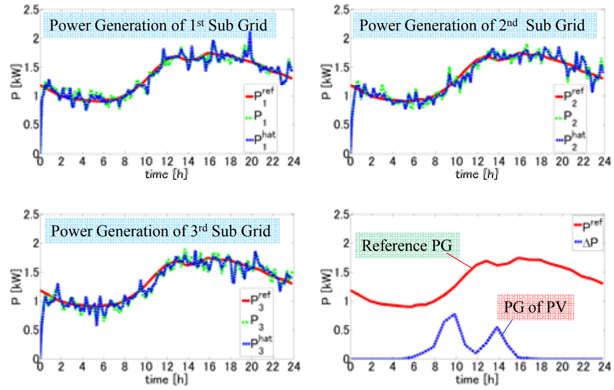
Application to Simplified Micro Grid



- Parameters

$$\Xi = 0.3 \quad \forall i, j \in \{1, 2, 3\} \quad Q = I \quad P_{xx} = I \quad N_C = 2$$

Numerical Simulation



Conclusion and Future Works

- **Conclusion**
  - Electric Demand Prediction
  - Predictive Control for Systems with Information Structure
  - Derived a Solution to Constrained Finite-Time Optimal Control
  - Moving Horizon Estimation Problem for Systems with IS
  - Numerical Simulation for Micro Grid show the effectiveness of the proposed Method
- **Future Problems**
  - Mixture of Demand Prediction and Predictive Control
  - Plug and Play Control

Appendix

Some Previous Works and Goal

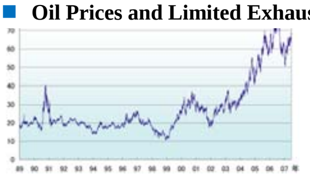
- ARMA(Autoregressive Moving Average) Model
  S.Sp.Pappas (2009)
- Neural Network Approach
  Ishida (1994)
- Kalman Filter Approach
  H.M.Al-Hamadi (2004)
- **Goal of this Research**
  - Achieve more accurate prediction of short-term electrical power demand based on $\mathcal{H}_\infty$ filter
  - Develop simple data allocation based on demand curve

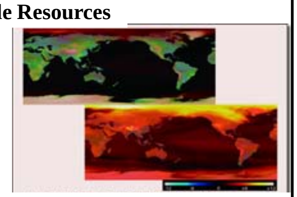
Several Related Previous Works

- **Important Related Works**
  - Optimality for Information Structure
    M. Rotkowitz, S. Lall, B. Bamieh, P. G. Voulgaris
  - LQG with Information structures by covariance constraints
    A. Rantzer
  - Dual Decomposition
    A. Rantzer
  - Distributed Consensus Algorithm
    R. Olfati-Saber
  - Receding Horizon Control and Moving Horizon Estimation
    D. Q. Mayne, J. B. Rawlings, C. V. Rao

Environmental and Energy Problems

- **Oil Prices and Limited Exhaustible Resources**

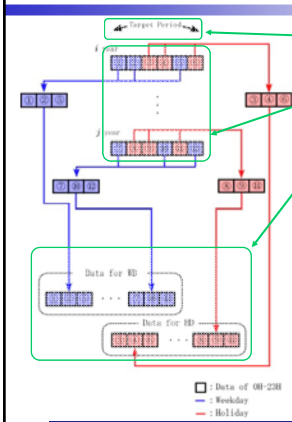




- **CO2 Emission and Global Warming**

- **Distributed and Uncontrollable Energy Source**

Parameter Estimation based on Demand Curve



- Check the past Data of the Corresponding Target Period in Several Years
- Divide the Past Data into **Weekday** and **Weekend -Holiday** Data
- Make Sequential Data made by only **Weekday** and **Weekend -Holiday** Data
- Parameter Estimation for **WD** and **WEHD** via Filtering

⇩

WD and **WEHD** Model

- Support Vector Machine
- Just-In-Time Modeling

could be applied

Remark

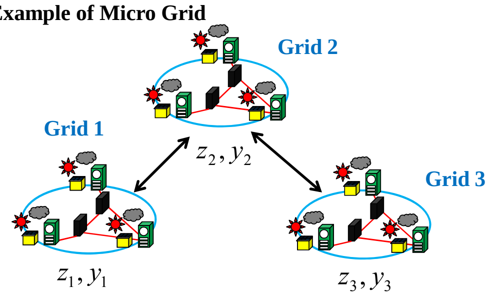
- **Distributed Solution**

  Using a dual decomposition technique makes it possible to find a solution in a distributed fashion.

  M. D. Mesarovic, I. Lefkowitz and J. D. Pearson, ``Advances in Multilevel Control,'' Proc. of the IFAC Symposium, 1965.

Interconnections of Micro Grid Subsystems

- **An Example of Micro Grid**



z_i : Total power of the *i-th* subsystem

y_i : Total output of the *i-th* subsystem

Dynamical Model of Micro Grid

- **An Example of Micro Grid**

$$\begin{bmatrix} z_1(t+1)-z_1^{ref}(t+1) \\ z_2(t+1)-z_2^{ref}(t+1) \\ z_3(t+1)-z_3^{ref}(t+1) \end{bmatrix} = \begin{bmatrix} \Xi_{11} & \Xi_{12} & 0 \\ \Xi_{21} & \Xi_{22} & \Xi_{23} \\ 0 & \Xi_{32} & \Xi_{33} \end{bmatrix} \begin{bmatrix} z_1(t)-z_1^{ref}(t) \\ z_2(t)-z_2^{ref}(t) \\ z_3(t)-z_3^{ref}(t) \end{bmatrix} + \begin{bmatrix} u_1(t) \\ u_2(t) \\ u_3(t) \end{bmatrix} + \begin{bmatrix} w_1(t) \\ w_2(t) \\ w_3(t) \end{bmatrix} + \begin{bmatrix} \Delta z_1(t)-z_1^{ref}(t+1) \\ \Delta z_2(t)-z_2^{ref}(t+1) \\ \Delta z_3(t)-z_3^{ref}(t+1) \end{bmatrix}$$

$$\begin{bmatrix} y_1(t) \\ y_2(t) \\ y_3(t) \end{bmatrix} = \begin{bmatrix} z_1(t)-z_1^{ref}(t) \\ z_2(t)-z_2^{ref}(t) \\ z_3(t)-z_3^{ref}(t) \end{bmatrix} + \begin{bmatrix} v_1(t) \\ v_2(t) \\ v_3(t) \end{bmatrix} \quad (4)$$

where
- $z_i(t)$ Total power of the *i-th* subsystem
- $u_i(t)$ power generated by the *i-th* micro gas turbine (controllable)
- $\Delta z_i(t)$ *i-th* photo-voltaic generator (uncontrollable)
- $z_i^{ref}(t)$ Desirable power of *i-th* subsystem
- $w_i(t)$ $v_i(t)$ zero mean white noises

It takes 1 time step for information to be passed from a subsystem to neighbors.

Dynamical Model of Micro Grid

Under the assumption of $z_i^{ref}(t) = \Delta z_i(t) = 0 \quad {}^{\forall} t \in Z_+$

$$\begin{bmatrix} z_1(t+1) \\ z_2(t+1) \\ z_3(t+1) \end{bmatrix} = \begin{bmatrix} \Xi_{11} & \Xi_{12} & 0 \\ \Xi_{21} & \Xi_{22} & \Xi_{23} \\ 0 & \Xi_{32} & \Xi_{33} \end{bmatrix} \begin{bmatrix} z_1(t) \\ z_2(t) \\ z_3(t) \end{bmatrix} + \begin{bmatrix} u_1(t) \\ u_2(t) \\ u_3(t) \end{bmatrix} + \begin{bmatrix} w_1(t) \\ w_2(t) \\ w_3(t) \end{bmatrix} \quad (5)$$

- In practical situations, such models are not obtained and only numerical data is available on-line.
- Predictive control allows us to include such future information available online into the control problem.

System with Information Structure

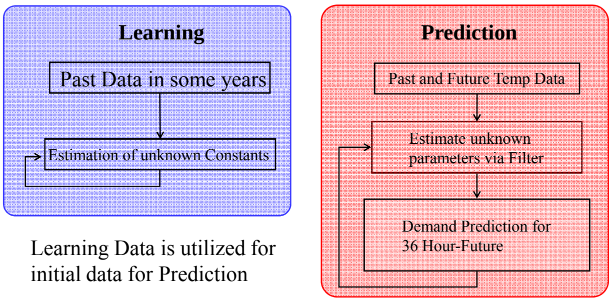
- Consider a system with information structures where each subsystem collects spatio-temporally different information.
- The information available for control and estimation differs from subsystem to subsystem, which should be included into the system model (1)
- Assume that information propagates through the communication channels at least as fast as it propagates through the plant itself (funnel causality) or partially nested information structure.

Outline

- **Electric Demand Prediction**
- **Predictive Control of Micro Grid**

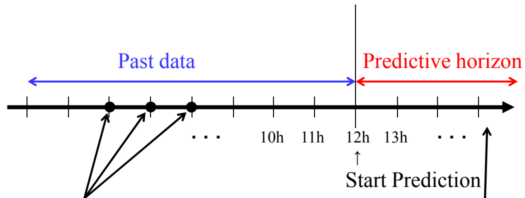
Electric Demand Prediction

- Learning : Estimate unknown constants based on past data set
- Prediction : Update unknown constants and prediction



Learning Data is utilized for initial data for Prediction

Problem Formulation



- Past demand information
- Past temperature information

in each hour

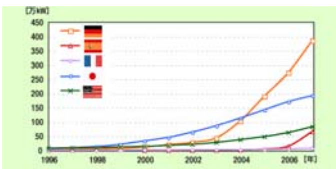
- Utilize future temperature information at predictive time from weather report

Environmental and Energy Problems

Environmental issues are currently one of the most important concerns to be globally tackled

- It is desired to generate and use clean energy
  wind-power generation, photovoltaic generation
  hydraulic power generation
  instead of fossil and exhaustible fuel electric power generation

http://cheapergreener.wordpress.com

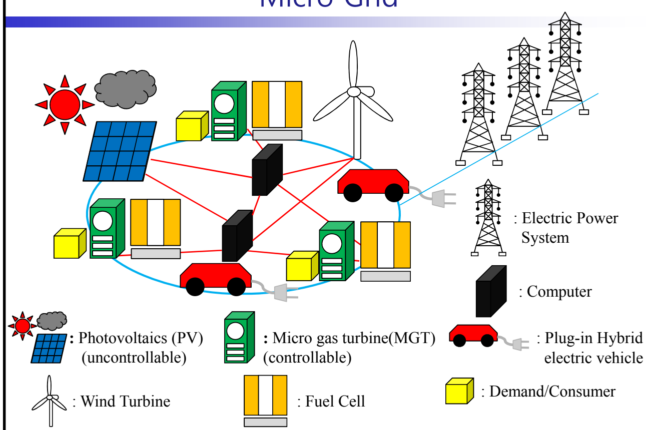


http://premium.nikkeibp.co.jp/

Some Remarks on Problem 1

- The present control law determines the control input according to the receding horizon control policy.
- The above problem with the initial state is solved, the first one of the computed control moves is implemented and the optimal control problem is newly solved at the next step.
- Choosing a small horizon *Nc* implies ignoring the effects of remote subsystems.

Micro Grid



Simulation Results : Parameter Estimation

- Parameters

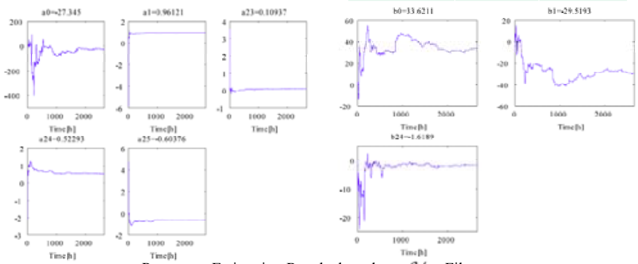
$R = 1$

$x(0) = [0\ 0\ 0\ 0\ 0\ 0\ 0\ 0]^T$

$P(0) = I_8$

γ

	Weekday	WE HD
Prediction A	9.8	9.8
Prediction B	9.7	9.7
Prediction C	9.7	9.7
Prediction D	9.6	9.6



Parameter Estimation Results based on $\mathcal{H}_\infty$ Filter