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Short-Term Wind Power Prediction for Wind Turbine via Kalman Filter based on JIT Modeling

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Abstract: This paper addresses wind power prediction which is known to be a key technology in EMS(Energy Management Systems). In recent years, an introductory expansion of renewable energy is expected and the prediction of wind power generation is needed for taking in wind power generation. The goal of this work is to predict the amount of generation in the next day from the past actual data and the weather forecast data of wind. In this paper, 24 hours ahead power prediction method using a filtering theory is proposed for wind power generation. The prediction method is a simple algorithm, the procedure of prediction consists of two steps, the data processing and the calculation of predicted values. In the data processing, in order to get the correlative data from the database, we employ JIT(Just-In-Time) Modeling. In the calculation of predicted value, we provide the regression model for wind speed and wind power, and the unknown parameters are estimated via constrained kalman filter. Finally, the advantages of the proposed method over the conventional method are shown through simulations.

Keywords: Short-term Prediction, Wind Power, Just-In-Time Modeling(JIT Modeling), Constrained Kalman Filter, Energy Management Systems(EMS)

1. INTRODUCTION

As one of several powerful tools to help address global warming, the study of renewable-energy-based smart grids is becoming popular. Smart grids provide renewable energy sources such as solar and wind, which cannot be controlled directly, and involve combinations of large-scale complex systems with various power generation and consumption systems [1].

In such a distribution system, the output of wind power generation is constantly controlled by the former. It is a method for controlling output such that the total amount of wind power output and battery charging and discharging become constant based on the predicted amount of power generation for the next day. Since errors are included in predicted values, to maintain advance notice values, an expensive storage battery is installed to alert the grid to lower predicted values when electricity production increases so that output can be restricted.

If an accurate predicted value of wind power is acquired, it is controllable as an advance notice. Moreover, if many predicted values can be updated, then when prediction is separated, it will become possible to change an advance notice value.

Being able to accurately predict hourly wind speed variations is important for utilities to properly plan their energy resource portfolio mix. Finally, knowledge of short-term wind speed variations, such as gusts and turbulence, is important in both turbine and control design processes so that structural loading can be mitigated during these events [2].

Conventional wind power prediction techniques can be divided roughly into two categories: methods based on a physical model, such as Numerical Weather Prediction (NWP), and methods based on statistics, such as that provided by an Autoregressive Moving-Average (ARMA) model. The former is a technique for predicting future data from past measurement data. Techniques based on ARMA models such as the Box-Jenkins model [3] and neural networks [4] [5] have been studied actively. Kanna [6] and Kusiak [7] predicted wind speed and power generation by using a neural network. Fujimura [8] built a 9-h-ahead wind power prediction model that uses fuzzy control by using the GPV data of a mesoscale model delivered by the Japan Meteorological Business Support Center. Louka [9] researched wind power prediction using the Kalman filter. Hosoda [10] considered solar power prediction using the Kalman filter, but compared with solar power, wind power prediction is difficult.

In this paper, a method for statistically rectifying forecast values based on the literature [10] is used. Since it is a prediction method which can be predicted from little data as a feature of the literature 8, it is useful to the wind power prediction which change of a power generation output is large and sufficient quantity of data cannot obtain. By the proposal method, regression equation expresses a wind speed model and a wind power model, and it estimates a strange coefficient with constrained Kalman filter from past wind speed data and the wind power data. As a feature of the proposed method, noise is assumed to help improve the prediction accuracy of the setup of the Kalman gain that serves to set the minimum prediction error. Wind speed data with the correlation acquired by JIT modeling [11] is substituted for a wind speed model, a statistical work is carried out, and the strange coefficient parameter of a model is learned and estimated. By using this method, exact estimation of the error of a parameter can be made so that it is suitable for research purposes. A wind power calculated value is then calculated by applying the wind speed predicted using the model with a small error to a power curve. After calculating a wind power calculated value, wind power prediction is calculated from a wind power model. As a feature of the proposal technique, the reliability of prediction is explicitly guaranteed by strange coefficient estimation, and there is a point of performing prediction from enough little data. At the last, the validity of wind power prediction using JIT modeling and the constrained Kalman filter in this paper is compared with results from the literature [6].

2. PROBLEM FORMULATION

First, the weather forecast data of wind speed, the past data of the wind speed, and wind power data are stored in a database by two months. The data which has correlation with the weather forecast data at predicting point in the database is chosen by JIT modeling, and the wind speed and wind power data corresponding to the data are found. The wind speed data acquired by JIT modeling and the weather forecast data of wind speed are substituted into a wind speed model. Then a statistical analysis is carried out and the strange coefficient parameter of the model is estimated. Based on wind speed prediction value which is more highly precise than the weather forecast, the wind power is calculated. The wind power data acquired by JIT modeling and wind power calculated value by experimental power curve are substituted into a wind power model, and the same statistical analysis as a wind speed model is carried out to estimate the strange coefficient parameter of a model.

The process of prediction is shown in Fig. 1.

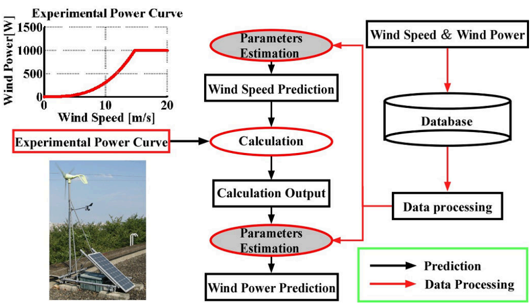


Fig. 1 Wind power prediction process[12]

2.1 Prediction Model

2.1.1 Wind Speed Prediction

The wind speed value acquired by the anemometer which is beside an wind turbine installed on the roof of Keio University, Yagami Campus Building 25 is used. The data sampling time is 1 h. The wind speed data of a weather forecast uses the weather forecast delivered to the Japan Meteorological Business Support Center, etc. Eight forecasts are carried out per day, four of which have periods of 33 h and four of which have periods of 15 h. At this center, every hour is predicted 33 h ahead. The wind speed model using the weather forecast and neighborhood data acquired by JIT modeling uses the following equation:

$$v_{t+1|t} \;=\; a_t v^{JIT}_{t-23|t} + b_t v^{f}_{t+1|t} \qquad (1)$$

$v^{JIT}_{t-23|t}$[m/s] is wind speed data in the time of the neighborhood data acquired by JIT modeling. $v^{f}_{t+i|t}$[m/s] expresses the forecast value of the i-hour-ahead wind speed based on data at time t. a_t, b_t are wind speed coefficients. A strange correlation coefficient is estimated from this model by using the Kalman filter algorithm.

2.1.2 Wind Power Generator

The data used are meteorological data of the wind speed in Yokohama from the Meteorological Agency and weather forecast data of wind speed. Further, it is assumed that the wind power data in the prediction are from the turbine installed on the roof of Keio University. The parameters of the wind power generator (Z-1000) are listed in Table 1.

Table 1 Parameter of wind turbine(Z-1000)

Blade Radius	1.8[m]
Rated Output	1000[W](12.5m/s)
Rotation Start Wind Speed	0[m/s]
Generation Start Wind Speed	2.5[m/s]
Maximum Output	2300[W](20m/s)

The relation between the average wind speed and wind power output is plotted in Fig. 2.

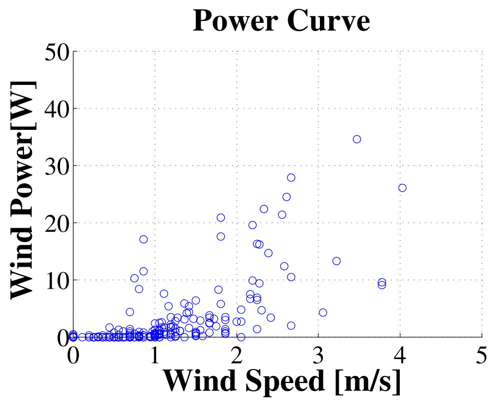


Fig. 2 Relation between Wind Power and Wind Speed

Before rotation starts, a wind of more than 1.5 [m/s] is blowing on average. Therefore, when deriving a power curve, one must take into consideration both the maximum power output as well as the rotation start wind speed.

2.1.3 Experimental Power Curve

Generally, a power curve is denoted by the equation of the power output to wind speed. However, the power curve is the power generation output of average wind speed per hour. Therefore, we have to construct a power curve from the data of power output and the surveyed average wind speed per hour. This is considered as the experimental power curve.

2.1.4 Wind Power Prediction

The prediction model of wind power predicts power generation by substituting the value of the predicted wind speed into the experimental power curve. The wind

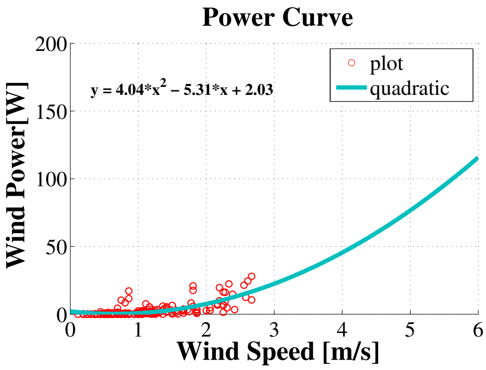


Fig. 3 Experimental Power Curve

power model using the calculated value and neighborhood data acquired by JIT modeling uses the following equation:

$$p_{t+1|t} = c_t p^{JIT}_{t-23|t} + d_t f_{pc}(v_{t+1|t}) \quad (2)$$

$$f_{pc}(v_{t+1|t}) = 4.04 v^2_{t+1|t} - 5.31 v_{t+1|t} + 2.03 \quad (3)$$

$p_{t|t}$[W] is the observed value of output at time t. $p^{JIT}_{t-23|t}$[W] is wind power data in the time of the neighborhood data acquired by JIT modeling. $f_{pc}(\cdot)$[W] is a function of the power curve of the wind power generator. $\hat{p}_{t+1|t}$[W] is the predicted value of wind power output 1 h ahead of time t. c_t, d_t are strange correlation coefficients. A strange correlation coefficient is estimated from this model by using the Kalman filter algorithm.

2.2 Prediction Algorithm

The algorithm that estimates the wind speed coefficient parameter is now described. The following discrete-time state space expressions are used for parameter estimation:

$$\begin{aligned} \boldsymbol{x}_{k+1|k} &= \boldsymbol{A}_k \boldsymbol{x}_{k|k} + \boldsymbol{w}_k \\ v_{k|k} &= \boldsymbol{C}_k \boldsymbol{x}_{k|k} + r_k \end{aligned} \quad (4)$$

where $\boldsymbol{x}_{k|k} \in \mathbb{R}^{n_x}$ is a state vector to be estimated in step k and is defined by the matrix of the following coefficients:

$$x_{k|k} = \left[\begin{array}{cc} a_k & b_k \end{array}\right]^T \quad (5)$$

$\boldsymbol{C}_k \in \mathbb{R}^{n_x}$ is a time-varying output vector and is considered to have the following values:

$$C_k = \left[\begin{array}{cc} v^{JIT}_{k|k} & v^{f}_{k+1|k} \end{array}\right] \quad (6)$$

$\boldsymbol{A}_k \in \mathbb{R}^{n_x}$ is set up as follows:

$$\boldsymbol{A}_k = \boldsymbol{I} \quad (7)$$

$k \in \mathbb{Z}_+$ is a step and $y_{k|k} \in \mathbb{R}$ is an observed value; $\boldsymbol{w}_k \in \mathbb{R}^{n_x}$ and $v_k \in \mathbb{R}^{n_x}$ express the process noise and the measurement noise, respectively. The noise is assumed to be white Gaussian:

$$E\left\{\left[\begin{array}{c} w_k \\ r_k \end{array}\right]\left[\begin{array}{cc} w_l^T & r_l^T \end{array}\right]\right\} = \left[\begin{array}{cc} W_k & 0 \\ 0 & R_k \end{array}\right]\delta_{kl} \quad (8)$$

Moreover, the covariance matrices $V_k \in \mathbb{R}$ and $W_k \in \mathbb{R}$ are known. The Kalman filter algorithm for estimating a coefficient using the above equation can be acquired by the following recursive calculations. Based on Equations (3)–(6), a parameter is estimated according to the following steps:

1. Renew the Kalman gain:

$$K_k = \left[\boldsymbol{P}_{k|k-1}\boldsymbol{C}_k^T\right]\left[\boldsymbol{C}_k\boldsymbol{P}_{k|k-1}\boldsymbol{C}_k^T + W_k\right]^{-1} \quad (9)$$

2. Renew the state estimated value:

$$\hat{\boldsymbol{x}}_{k|k} = \hat{\boldsymbol{x}}_{k|k-1} + K_k\left[y_k - \boldsymbol{C}_k\hat{\boldsymbol{x}}_{k|k-1}\right] \quad (10)$$

3. Renew the estimated covariance matrix:

$$\boldsymbol{P}_{k|k} = \boldsymbol{P}_{k|k-1} - K_k\boldsymbol{C}_k\boldsymbol{P}_{k|k-1} \quad (11)$$

where $\boldsymbol{P}_k \in \mathbb{R}^{n_x \times n_x}$ is the estimated covariance matrix in step k and $K_k \in \mathbb{R}$ is the Kalman gain. Then, $\hat{x}_{k|k-1}$ is the estimate of the coefficient calculated with the data before each step. Equation (5), which is a coefficient of Equation (1), can be estimated by repeating the above process 1–3 two or more times.

2.3 Prediction Aim

Mean absolute error (MAE) is used to evaluate the prediction result of wind speed:

$$\mathrm{MAE} = \frac{1}{24}\sum_{i=1}^{24}||v_{t+i|t+i} - \hat{v}_{t+i|t+i-1}|| \times 100[\%] \quad (12)$$

where $v_{t|t}$ is an actual measurement, $\hat{v}_{t+1|t}$ is the model estimate, and $N \in \mathbb{Z}_+$ shows the number of data points. Wind power prediction is evaluated by using the mean relative error (MRE):

$$\mathrm{MRE} = \frac{1}{W_{total}}\frac{1}{24}\sum_{i=1}^{24}||p_{t+i|t+i} - \hat{p}_{t+i|t+i-1}|| \times 100[\%] \quad (13)$$

where $p_{t|t}$ is an actual measurement, $\hat{p}_{t+1|t}$ is the model estimate, W_{total} is the rated output, and N is the number of data points. In the case of the short-term prediction in this paper, the prediction is evaluated by the mean absolute error of the wind speed every hour up to 24 h ahead.

3. DATA PROCESSING BASED ON JIT MODELING

As observational data, wind speed data, the wind speed data of a weather forecast, and wind power data are treated, and it predicts the wind speed or the wind power by picking out data with high correlativity from the past data by using JIT modeling to these data. JIT modeling arranges the wind speed and the wind power data in a sequence that correlativity is high using weather forecast data. The classified data is used for strange coefficient estimation, and is required for highly precise prediction.

Although general JIT modeling is a control rule which gives the control input which makes the deviation of a reference value and an output small in real time, in this paper a reference value does not exist on the problem dealt with. So, in the wind power prediction, the output of the future is predicted based on the data by the present. This section explains JIT modeling as the data-processing method of the weather forecast, wind speed data, and wind power data stored in the database.

First, the wind power JIT model is expressed with the system shown below.

$$\boldsymbol{y}^{JIT}_\tau = g(\boldsymbol{x}^{JIT}_\tau), \tau = 0, 1, 2 \quad (14)$$

$\boldsymbol{x}[\tau] \in \mathbb{R}^{\nVdash\times\nvDash}$ is a regression vector here,

$$\boldsymbol{x}_\tau^{JIT} = [v_{\tau+1}^f, \cdots, v_{\tau+24}^f] \quad (15)$$

$\boldsymbol{y}_\tau^{JIT}$ is the following outputs,

$$\boldsymbol{y}_\tau^{JIT} = [v_{\tau+1}, \cdots, v_{\tau+24}, p_{\tau+1}, \cdots, p_{\tau+24}] \quad (16)$$

$\boldsymbol{y}_\tau^{JIT} \in \mathbb{R}^{\nVdash\times\nvDash\nleftarrow}$ in which the wind power and wind speed at the time τ are dependent on the input v^f (weather forecast value of wind speed) to 24 step point. The aim of this paper is to predict 24-h ahead after the time τ of the output $\boldsymbol{y}^{JIT}$ from a wind speed forecast. The requiring point $\boldsymbol{\phi}_\tau \in \mathbb{R}^{\nVdash\times\nvDash}$ in time to predict is defined as the following vectors constituted by the wind speed forecast value.

$$\boldsymbol{\phi}_\tau = [v_{\tau+1}^f, \cdots, v_{\tau+24}^f] \quad (17)$$

The past information vector to which distance with this requiring point becomes the smallest is

$$\boldsymbol{\psi}_{i_{opt}} = [v_{i_{opt}+1}^{Model}, \cdots, v_{i_{opt}+24}^{Model}] \quad (18)$$

This is found out of a database and

$$\hat{\boldsymbol{y}}_{i_{opt}}^{JIT} = [v_{i_{opt}+1}, \cdots, v_{i_{opt}+24}, p_{i_{opt}+1}, \cdots, p_{i_{opt}+24}] \quad (19)$$

the above neighborhood data is acquired. Moreover, with an algorithm, a database is treated as the matrix $\boldsymbol{D}$ which has $[\boldsymbol{\psi}_i \boldsymbol{y}_i^{JIT}]$ as an element. For example, when output data of N group recorded in a different situation is given,

$$\{v_\tau^f)|\tau = 1, \cdots, N\} \quad (20)$$

the matrix $\boldsymbol{D} \in \mathbb{R}^{\mathbb{N}\times\nVdash}$ is as follows.

$$\boldsymbol{D} = \begin{bmatrix} \boldsymbol{\psi}_1 & \boldsymbol{y}_1^{JIT} \\ \vdots & \vdots \\ \boldsymbol{\psi}_N & \boldsymbol{y}_N^{JIT} \end{bmatrix} \quad (21)$$

However, $\boldsymbol{\psi}_i$ and $\boldsymbol{y}_i^{JIT}$ are

$$\begin{aligned} \boldsymbol{\psi}_i &= [v_{i+1}^f, v_{i+2}^f, \cdots, v_{i+24}^f] \\ \boldsymbol{y}_i^{JIT} &= [v_{i+1}, \cdots, v_{i+24}, p_{i+1}, \cdots, p_{i+24}] \quad (22) \end{aligned}$$

The algorithm of JIT modeling is summarized into below.

$$\hat{\boldsymbol{y}}_{i_{opt}}^{JIT} = JIT(D, \boldsymbol{\phi}_\tau, i_{opt}) \quad (23)$$

Step1:Rearrangement of an information vector

Standardized Euclidean distance d defines the distance of the information vectors $\boldsymbol{\phi}_\tau$ and $\boldsymbol{\psi}_i$,

$$d(\boldsymbol{\phi}_\tau, \boldsymbol{\psi}_i) = \sqrt{(\boldsymbol{\phi}_\tau - \boldsymbol{\psi}_i)W^{-1}(\boldsymbol{\phi}_\tau - \boldsymbol{\psi}_i)^T} \quad (24)$$

The matrix $\boldsymbol{D}$ is rearranged into an ascending order. An weighting matrix shows $\boldsymbol{W}$ below.

$$\boldsymbol{W} = \left[\mathrm{diag}\left(\frac{1}{l}\sum_{i=1}^{l}(\psi_i - \bar{\psi})^T(\psi_i - \bar{\psi})\right) \right] \quad (25)$$

$$\bar{\psi} = \frac{1}{l}\sum_{i=1}^{l}\boldsymbol{\psi}_i \quad (26)$$

l is a degree of $\boldsymbol{D}$ here and $\mathrm{diag}(\boldsymbol{A})$ expresses the operator which sets all the non-diagonal components of the matrix $\boldsymbol{A}$ to 0. $\boldsymbol{W}$ is a diagonal matrix of the l row l column whose j-th diagonal element is $s(j)$, and s is a scalar of standard deviation.

Step2:A setup of i_{opt}

$\boldsymbol{\psi}_{i_{opt}}$ which is i_{opt}-nearest neighbor of $\boldsymbol{\phi}_\tau$ is defined.

$$\boldsymbol{\psi}_{i_{opt}} := \{\boldsymbol{\psi}_i | i = 1, \cdots, k_{opt}\} \quad (27)$$

Step3:Calculation of $\hat{\boldsymbol{y}}_{i_{opt}}^{JIT}$

The output of $\boldsymbol{y}_i^{JIT}$ corresponding to i_{opt}-nearest neighbor is set to $\hat{\boldsymbol{y}}_{i_{opt}}^{JIT}$.

$$\hat{\boldsymbol{y}}_{i_{opt}}^{JIT} = \boldsymbol{y}_{i_{opt}}^{JIT} \quad (28)$$

4. CONSTRAINED KALMAN FILTER

This section describes strange coefficient estimation based on a constrained Kalman filter. First, the problem of the Kalman filter in strange coefficient estimation is explained. Next, the constrained Kalman filter algorithm for solving a problem is proposed.

4.1 The problem of a Kalman filter

The prediction result of Fig. 4 shows that the unusual value which lowers predictive accuracy exists. It is

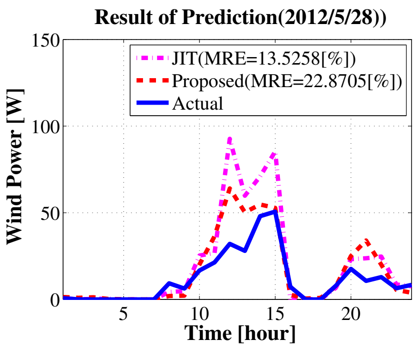


Fig. 4 Outlier of wind power prediction(5/28)

thought that the causes with this unusual main value are in the mis-prediction at the time of wind speed prediction, and it is possible that when the value of a weather forecast is too large as a cause, the value of wind speed prediction shifts. When this unusual value could be rectified well, it thought that performance became good, and the algorithm is proposed. The past data showed that it was 55.3 [W] about the maximum wind power of the actual measurement, and the maximum wind speed which counted the value backward from the power curve is set to 5.15 [m/s]. As mentioned above, the estimation problem in this paper is defined as the following problem 1.

Problem 1

A predicted value should detect the predicted value such as $\hat{y}_k > y_{max}$, and propose the algorithm which gives the predicted value whose reliability is still higher to the predicted value to which reliability fell.

v_{max}[m/s] is proposed for the wind speed maximum, the wind power maximum as p_{max}[W], and the following algorithms are proposed.

4.2 The algorithm of a constrained Kalman filter

A wind speed model is made into an example and a constrained Kalman filter is proposed by Equations (29)-(35).

Step1.Prediction

$$\hat{v}_{k|k-1} = \boldsymbol{C}_k \hat{\boldsymbol{x}}_{k|k-1} \tag{29}$$

Step2.Detection/Compensation

$$\hat{v}_{k|k-1} = \begin{cases} v^{max} & \hat{v}_{k|k-1} > v_{max} \\ \hat{v}_{k|k-1} & \hat{v}_{k|k-1} < v_{max} \end{cases} \tag{30}$$

Step3.Calculation of error covariance matrix $P_{k|k-1}$

$$\boldsymbol{P}_{k|k-1} = \boldsymbol{A}_k \boldsymbol{P}_{k-1} \boldsymbol{A}_k^T + \boldsymbol{W}_k \tag{31}$$

Step4.Calculation of Kalman gain

$$K_k = \boldsymbol{P}_{k|k-1} \boldsymbol{C}_k^T [\boldsymbol{C}_k \boldsymbol{P}_{k|k-1} \boldsymbol{C}_k^T + R_k]^{-1} \tag{32}$$

Step5.Correction with error of a predicted value

$$\hat{\boldsymbol{x}}_{k|k} = \hat{\boldsymbol{x}}_{k|k-1} + K_k (v_k - \boldsymbol{C}_k \hat{\boldsymbol{x}}_{k|k-1}) \tag{33}$$

Step6.Correction of state estimation matrix

$$\hat{\boldsymbol{x}}_{k+1|k} = \boldsymbol{A}_k \hat{\boldsymbol{x}}_{k|k} \tag{34}$$

Step7.Correction of error covariance matrix

$$\boldsymbol{P}_{k|k} = \boldsymbol{P}_{k|k-1} - K_k \boldsymbol{C}_k \boldsymbol{P}_{k|k-1} \tag{35}$$

A strange coefficient can be estimated taking restrictions into consideration by carrying out repetitive calculation of Steps1-7.

As mentioned above, the Theorem 1 is realized to the problem 1.

Theorem 1

The following relations are realized between the observation error covariance $S_k = cov(v_k - \hat{v}_{k|k-1})$ of a common Kalman filter and the observation error covariance $S_k^{max} = cov(v_k - v_{max})$ in a Kalman filter algorithm the time of a predicted value being set to $\hat{v}_{k|k-1} > v_{max}$.

$$S_k^{max} < S_k \tag{36}$$

Proof: Observed value v_k is,

$$0 \leq v_k \leq v_{max} \tag{37}$$

About the predicted value $\hat{v}_{k|k-1}$, when it is $\hat{v}_{k|k-1} > v_{max}$, the observation error covariance S_k is

$$\begin{aligned} S_k &= cov(v_k - \hat{v}_{k|k-1}) \\ &= E[(v_k - \hat{v}_{k|k-1} - E[v_k - \hat{v}_{k|k-1}]) \\ &\qquad (v_k - \hat{v}_{k|k-1} - E[v_k - \hat{v}_{k|k-1}])^T] \end{aligned} \tag{38}$$

At this time, if it sets with $\hat{v}_{k|k-1} = v_{max}$, the observation error covariance S_k^{max} is.

$$\begin{aligned} S_k^{max} &= cov(v_k - v_{max}) \\ &= E[(v_k - v_{max} - E[v_k - v_{max}]) \\ &\qquad (v_k - v_{max} - E[v_k - v_{max}])^T] \end{aligned} \tag{39}$$

The observation error covariances S_k and S_k^{max} are compared.

$$|v_k - v_{max}| < |v_k - \hat{v}_{k|k-1}| \tag{40}$$

Therefore, Equation (41) is realized.

$$\begin{aligned} S_k^{max} - S_k &= E[(v_k - v_{max} - E[v_k - v_{max}]) \\ &\qquad (v_k - v_{max} - E[v_k - v_{max}])^T] \\ &\quad -E[(v_k - \hat{v}_{k|k-1} - E[v_k - \hat{v}_{k|k-1}]) \\ &\qquad (v_k - \hat{v}_{k|k-1} - E[v_k - \hat{v}_{k|k-1}])^T] \\ &< 0 \end{aligned} \tag{41}$$

Therefore, the following equation can be drawn.

$$S_k^{max} < S_k \tag{42}$$

As mentioned above, in $v_{max} < \hat{v}_{k|k-1}$, the improvement in predictive accuracy can be attained by transposing v_{max} to $\hat{v}_{k|k-1}$. ■

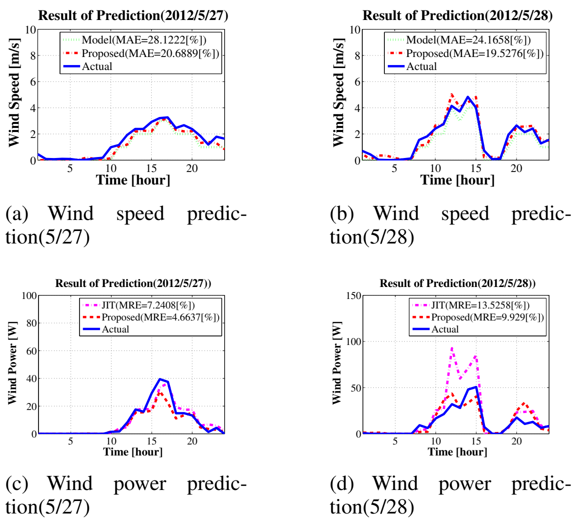
5. WIND POWER PREDICTION

5.1 Prediction conditions

Wind speed prediction predicts wind speed using the data of the wind speed value acquired with the actual anemometer which is beside the wind turbine installed in Keio University, and the weather forecast of Yokohama. Wind power prediction uses the output data per hour of the same wind turbine. The data to treat are average wind speed and wind power data of the time series per hour from March 1 to May 31, 2012. The data volume is compressed into the same quantity, i.e., 20 days. The prediction results on condition of above is shown from the following paragraph.

5.2 Prediction result

The prediction results of the power output for 24 h on May 27 and 28, 2012, are shown in Fig. 5. As for both wind speed prediction and wind power prediction, noises are $W_k = 0.01$, $R_k = 0.01$, a state estimation value is $x_0 = \begin{bmatrix} 1/2 & 1/2 \end{bmatrix}^T$, and the initial value of a state error covariance matrix is $P_0 = I$, respectively.



(a) Wind speed prediction(5/27)

(b) Wind speed prediction(5/28)

(c) Wind power prediction(5/27)

(d) Wind power prediction(5/28)

Fig. 5 Prediction result

The view of the above figure divided and explained to wind speed and wind power prediction. In wind speed prediction, a green dotted line is a value of a weather forecast, a red alternate long and short dash line is a predicted value, and a blue solid line is an actual measurement. The line of green and red seems to follow in change of a blue line, respectively. Moreover, when the value of the error rate MAE with an actual measurement is seen in each figure, it turns out that each has acquired the more accurate wind speed predicted value than the wind speed of a weather forecast.

Next, in wind power prediction, a purplish red alternate long and short dash line is a value of the neighborhood data acquired by JIT modeling, a red dotted line is a prediction result with the proposal technique, and a blue solid line is an actual measurement. From the result, the error rate MRE of the proposal technique on May 27 and 28, 2012, are set to 4.66% and 9.92%, respectively. Even if it compares this to a rate of an average prediction error on the 1 day called literature [6] (7.08%), it is improving. Moreover, about the result of May 28, it can also check that the predicted value is compensated with the constrained Kalman filter.

5.3 Evaluation of prediction

The evaluation as a result of the wind power prediction for one week from May 25 to 31, 2012 is summarized in Table 2.

Table 2 Evaluation(Wind power)

	Error[%]
Referrence[11]	17.87
Calculation	11.01
JIT	7.92
proposed	6.41

Evaluation shows that the accuracy of prediction by the proposal technique is good. Rather than the neighborhood data acquired by JIT modeling, and the value calculated by experimental power curve from wind speed predicted value, the proposal technique is a value with few errors with an actual measurement. Moreover, our maximum error rate (MRE) of 6.41% is lower than that from the literature [6] (7.08%), demonstrating the improved accuracy of the proposed technique.

6. CONCLUSIONS

In this paper, wind speed data was independently measured from wind power turbines and wind power predictions with constrained Kalman filter were performed. Data processing was carried out using JIT modeling, and data was used as data with high correlativity. By having built the model using this data, rather than the conventional method, there are little data and computational complexity and they have compensated the reliability of prediction with the proposing method in the past.

Evaluation of the prediction result for one week, compared with those of the conventional method [6] for one day exhibited slightly greater accuracy for one week. Moreover, the error rate (MRE) improved by 0.67% over that from conventional methods. The validity of the proposed technique was confirmed from these results.

I would like to tackle predictive accuracy and the improvement in reliability by proposing the algorithm to converge a state vector in strange coefficient estimation, and the proof of monotone decreasing of state error covariance matrix as a future work.

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