A METHOD FOR REVISING TEMPERATURE AND HUMIDITY PREDICTION USING ADDITIONAL OBSERVATIONS AND WEATHER FORECASTS

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ABSTRACT

Weather prediction is considered to be essential for the predictive control of HVAC systems in which dynamic components, such as a thermal storage tank or heavy building envelope, exist. This paper proposes a method for revising the prior prediction of ambient temperature and humidity by combining two additionally available different data sources, i.e., observations at the building site and forecasts from a weather station. The proposed method applies the theory of orthogonal projection employed in the Kalman filter, and the revised predictions are statistically optimal for determining the minimum-variance linear estimate.

KEYWORDS

Weather prediction, Ambient temperature, Ambient humidity, Estimation theory

INTRODUCTION

Predictive control is applied to a dynamic system in which prior decisions are required for achieving better performance. For HVAC applications, plant scheduling for thermal storage system is a representative example of the predictive control. The effect of predictive control is influenced by the prediction accuracy of ambient weather conditions that strongly affect the thermal status of the building such as internal temperature or cooling/heating loads.

In the past, several methods have been proposed for predicting ambient temperature, ambient humidity, and solar radiation for thermal storage applications. Those methodologies are classified into three categories: (1) using observations only at the building site, (2) methods that use forecasts obtained from a local weather stations only, and (3) methods that use both observations and forecasts. Ren et al. (2002) tried to correct predicted profiles using a forecast from a weather station, and found that the correction may increase prediction errors for nights and early mornings (short lead time) because the initial prediction errors are originally small during this period. They suggest that updating using observations is effective in improving predictions for the short lead time and corrections for daytime profile; further, it might be effective to combine correction and updating. With regard to accuracy, it is preferable to use both observations and forecasts from a weather station. However, no previous research in the HVAC field has presented a statistically optimal method to combine this information, even if both observations and forecasts are used.

This paper aims to present a method that revises the "former prediction" of ambient temperature and ambient humidity by using additional observations and forecasts. A former prediction may be the initial prediction or a revised prediction with the proposed method. In this paper, "initial prediction" refers to the prediction derived by using a certain methodology (not covered in this paper). In order to maintain generality, it is not preferable to assume a certain type of methodology for the initial prediction. The method proposed in this paper accepts any methodology for the initial prediction if it uses past observations at the site. The revised predictions are considered to give the minimum-variance linear estimate according to the theory of orthogonal projection.

PREDICTION PROCEDURE

Figure 1 shows a sample procedure of the proposed prediction method. In this paper, "Correction" refers to the correction of the initial prediction profile by using the weather forecast of temperature and humidity obtained from a local weather station. "Updating" refers to updating previous predictions using an observation at the building site. The previous prediction may be an initial, corrected, or previously updated prediction. Typically, the initial prediction is made at a certain time in the evening when a weather forecast is available, and the prediction horizon is set to 24 h. However, it is possible to make an initial prediction every hour without the update. Each time an additional forecast is available, both the initial prediction and correction are made consecutively. The correction may be omitted if a forecast is not available at the time of the initial prediction.

CORRECTION AND UPDATING METHODOLOGY

The proposed method applies the theory of orthogonal projection employed in the Kalman filter

Time Origin	Prediction	Predicted Period	Data Source
k^*	Initial prediction	k^*+1,k^*+2,...,k^*+L	Observations up to k^*
	Correction	k^*+1,k^*+2,...,k^*+L	Forecast from a weather station
k^*+1	Updating	k^*+2,..., k^*+L	Observation at k^*+1
⋮	⋮	⋮	⋮
k^*+L-1	Updating	k^*+L	Observation at k^*+ L-1

Time elapse

Figure 1 Sample procedure of weather prediction

(Kalman 1960). The Kalman filter equations are classified into two groups: time update equations and measurement update equations (see Luenberger 1969). The latter equations correct an *a priori* estimate that is derived from all prior measurements in order to obtain an improved *a posteriori* estimate using a new measurement by the theory of orthogonal projection (see Appendix).

Correction using a forecast

The vector $\boldsymbol{x}$ in Equation (A-1) is set as

$$\boldsymbol{x} = [\theta_o(k^*+1), \theta_o(k^*+2), ..., \theta_o(k^*+L), \\ x_o(k^*+1), x_o(k^*+2), ..., x_o(k^*+L)]^{T\,T} \quad (1)$$

If the maximum lead time is 24 h ($L = 24$), the order of the above vector becomes 48 (the sampling interval is assumed to be 1 h in this paper). After the initial prediction is made, the *a priori* estimate of the vector $\boldsymbol{x}$ is expressed as

$$\boldsymbol{x} = [\bar{\theta}_o(k^*+1), \bar{\theta}_o(k^*+2), ..., \bar{\theta}_o(k^*+L), \\ \bar{x}_o(k^*+1), \bar{x}_o(k^*+2), ..., \bar{x}_o(k^*+L)]^T \quad (2)$$

where each element is the initial prediction value. The past initial prediction errors are used for the covariance $\bar{\boldsymbol{P}}$ in Equation (A-3). The element in row i and column j of $\bar{\boldsymbol{P}}$ is estimated as

$$\bar{P}_{i,j} = E[(x_i - \bar{x}_i)\cdot(x_j - \bar{x}_j)] \\ = \left\{\sum_{m=1}^{d}(x_i(k^* - 24m + i - \delta_i \cdot L) - \bar{x}_i(k^* - 24m)) \right. \\ \left. \cdot (x_j(k^* - 24m + j - \delta_j \cdot L) - \bar{x}_j(k^* - 24m))\right\}/d \quad (3)$$

where $x_i(t)$ is the observation of the ith element of $\boldsymbol{x}$ at time t; $\bar{x}_i(t)$, the initial prediction of the i th element of $\boldsymbol{x}$ predicted at origin time t ; m , the subscript for day; and d , the number of days required for the estimation. The flag δ_i is set to 0 for $i \le L$ and 1 for $i > L$. In other words, Equation (3) represents the statistical summary of the past initial prediction errors. A correction with a weather forecast is made by assuming the forecasted value as an additional observation $\boldsymbol{y}$ in Equation (A-1). First, the initial prediction must be made at the time of the correction. After the initial prediction, the forecasted values of temperature and humidity (if any) are set as the elements of $\boldsymbol{y}$. For example, if the weather forecast of the next day's minimum/maximum temperature, denoted by $\theta_{o,\min}$, $\theta_{o,\max}$, respectively, and the next day's minimum humidity ratio $x_{o,\min}$ is available at 6 p.m., the measurement vector $\boldsymbol{y}$ is

$$\boldsymbol{y} = [\theta_{o,\min}, \theta_{o,\max}, x_{o,\min}]^T \quad (4)$$

and the elements of the coefficient matrix $\boldsymbol{H}$ (3-by-2L in this case) in Equation (A-1) are

$$H_{i,j} = \begin{cases} 1 & (j = l(i)) \\ 0 & (\text{others}) \end{cases} \quad (5)$$

where $l(1) = 12$, $l(2) = 20$, and $l(3) = L + 20$. Here, $l(1) = 12$, i.e., $H_{1,12} = 1$, is obtained by assuming the forecast of the next day's minimum temperature, y_1 ($= \theta_{o,\min}$) as an observation of $\theta_o(k^* + 12)$ (the temperature after 12 h, i.e., 6 a.m.), disturbed with measurement noise v_1 (1st element of the vector $\boldsymbol{v}$ in Equation (A-1)). Therefore, the measurement noise coincides with the forecast error. The hour of day at which the minimum temperature occurs varies each day; however, in this case, the minimum temperature forecast is assumed to be the forecast for 6 a.m. The time should be changed according to the climate characteristics of each region. Similarly, in this case, the forecasts for the maximum temperature and minimum humidity ratio are assumed to be the forecasts for 2 p.m.

The covariance matrices $\boldsymbol{R}$ in Equation (A-2) and $\boldsymbol{S}$ in Equation (A-7) are also estimated by using the past forecasts and initial prediction errors, as in the case of $\bar{\boldsymbol{P}}$ in Equation (3). For example, the element of $\boldsymbol{R}$ is expressed as

$$R_{i,j} = E[v_i \cdot v_j] \\ = \left\{\sum_{m=1}^{d}(y_i(k^* - 24m) - x_{l(i)}(k^* - 24m + l(i) - \delta_{l(i)} \cdot L)) \right. \\ \left. \cdot (y_j(k^* - 24m) - x_{l(j)}(k^* - 24m + l(j) - \delta_{l(j)} \cdot L))\right\}/d \quad (6)$$

where $y_i(t)$ is the latest forecast available at time t and $x_{l(i)}(t)$ or $x_{l(j)}(t)$ is the corresponding observation value. A correction with a forecast is made by applying Equation (A-4) through (A-7) using the vectors and matrices defined as Equations (2) through (6). Because the measurement update equations provide the minimum-variance linear estimate of $\boldsymbol{x}$, the revised estimate $\hat{\boldsymbol{x}}$ obtained from Equation (A-4) incorporates a weather forecast into the initial prediction in order to obtain the optimal correction in terms of the error variances of the *a posteriori* estimate.

Updating using an observation

The state vector $\boldsymbol{x}$ can be revised with additional observations by using the same methodology as that for the correction using the forecast. The vector $\overline{\boldsymbol{x}}$ is defined in the same form as Equation (2). When the updating is applied to the results of the initial prediction, the elements become the initial prediction values. When the results of the former updating/correction are updated, the elements become the former *a posteriori* estimates. The covariance $\overline{\boldsymbol{P}}$ is also defined by Equation (3) when updating is applied to the results of the initial prediction. When applied to the results of the former updating/correction, the latest covariance $\hat{\boldsymbol{P}}$ is used as $\overline{\boldsymbol{P}}$. The vector $\boldsymbol{y}$ is the additional observation of the ambient temperature and humidity ratio

$$\boldsymbol{y} = [\theta_o, x_o]^T \tag{7}$$

The elements of the coefficient matrix $\boldsymbol{H}$ (2-by-2L in this case) are

$$H_{i,j} = \begin{cases} 1 & (j = L \cdot (i-1) + k - k^*) \\ 0 & (\text{others}) \end{cases} \tag{8}$$

where k is the current hour. $\boldsymbol{H}$ is set such that $\boldsymbol{Hx}$ coincides with the observation $\boldsymbol{y}$. The measurement error $\boldsymbol{v}$ in Equation (A-1) is neglected; therefore, the covariance matrices $\boldsymbol{R}$ and $\boldsymbol{S}$ are set to 0. The former prediction is updated by applying Equation (A-4) through (A-7) using the present observation.

VALIDATION USING OBSERVATION DATA

Weather and forecast data

In order to validate the proposed methodology, the weather data of the ambient temperature and humidity ratio in Tokyo, Japan, obtained from "expanded AMeDAS weather data" (Akasaka et al. 2003) are used. The data are processed from the "AMeDAS" (Automated Meteorological Data Acquisition System) data collected by Japan Meteorological Agency. Missing and abnormal values in the original data are added or corrected in the "expanded" version. Unobserved weather parameters such as solar radiation are also added. The validation period is one year—1990; however, the data of 1989 are also used for setting the initial condition.

Forecasts of the maximum/minimum temperature and minimum relative humidity are obtained from the Japan Meteorological Agency several times a day. In this validation, the forecast data of 1990 listed in Table 1 are used. All forecasts target the Tokyo region. "Assumed available hour" is the time when the correction is carried out in this validation test. "Assumed occurrence hour" is the time at which the forecasted value occurs hypothetically; it determines the setting of $\boldsymbol{H}$ in Equation 5. The value of the forecasted minimum relative humidity is converted into humidity ratio by using the latest forecasted temperature identified as the maximum temperature; this value considered to be the forecasted humidity ratio at 2 p.m.

It is commonly observed that the forecasts from a weather station differ from the maximum/minimum values of the local observations. This is because the ambient conditions vary even within the same forecasted area and the maximum/minimum values of the fixed-time interval observations become moderate in comparison with the real maximum/minimum values of a continuous time series. A simple linear regression is introduced to overcome this problem, as proposed by Yoshida (1997). For example, the revised forecast of the minimum temperature $\theta'_{o,\min}$ is derived from the original forecast, $\theta_{o,\min}$ as follows

$$\theta'_{o,\min} = a \cdot \theta_{o,\min} + b \tag{9}$$

where a and b are from the past realized data estimated by the least squares method.

Table 1. Forecasts data used for validation

Announced Hour	Assumed Available Hour	Item	Assumed Occurrence Hour
6:00 a.m.	6:00 a.m.	Today's daytime maximum temperature	2:00 p.m.
3:30 p.m.	6:00 p.m.	Tomorrow's minimum relative humidity	2:00 p.m.
6:00 p.m.	6:00 p.m.	Tomorrow's minimum temperature	6:00 a.m.
6:00 p.m.	6:00 p.m.	Tomorrow's maximum temperature	2:00 p.m.

Validation cases

Table 2 lists the validation cases. The initial prediction is made every hour except in cases 3 and 4 where it is made twice a day—at 6 a.m. and 6 p.m. Updating using the observation is carried out only at times at which the initial prediction is not made. This implies that updating is performed at all hours except 6 a.m. and 6 p.m. for cases 3 and 4, while it is not performed in the other cases. The initial prediction is corrected using forecasts at the time at which it is made with the exception of cases 1 and 3. The latest available forecast is used for the correction. For example, the forecast available at 6 p.m. is used for the correction at 9 p.m. Despite this rule, the forecast of "tomorrow's minimum relative humidity" available at 6 p.m. on the previous day is also used for the corrections made from 6 a.m. to 1 p.m. This is because of the lack of humidity-related forecasts during these periods. In case 5, the data storage period for estimating $\boldsymbol{\overline{P}}$, $\boldsymbol{R}$, and $\boldsymbol{S}$ is reduced from 60 days to 30 days. The period corresponds to d in Equation (3) or (6). In case 6, matrix $\boldsymbol{S}$ is set to be zero; this implies that the correlation between the errors in the initial predictions and those in the forecasts is ignored. In all cases, the value of L for the initial prediction is set to 48 h.

Table 2. Cases for validation (part 1)

Case No.	Initial Prediction	Correction Using Forecast	Data Storage	Covariance $\boldsymbol{S}$
1	Every hour	Not corrected	60 days	Considered
2	Every hour	Every hour	60 days	Considered
3	6 a.m. & 6 p.m.	Not corrected	60 days	Considered
4	6 a.m. & 6 p.m.	6 a.m. & 6 p.m.	60 days	Considered
5	Every hour	Every hour	30 days	Considered
6	Every hour	Every hour	60 days	Ignored

Initial prediction

The proposed method does not assume any specific methodology for the initial prediction under the condition that it only uses observations at a local site. Ren et al. (2002) or Henze et al. (2004) compared several prediction methods that do not use weather forecasts. Ren et al. (2002) have concluded that the DSM (deterministic-stochastic method) that uses EWMA model for the deterministic part and AR model for the stochastic part is relatively simple and can provide reasonably accurate results. The modified version of the DSM is employed for the initial prediction in these validation tests.

The daily profile of ambient temperature $\overline{D}_{tod}$ (*tod* = 1, 2, …, 24), which is the deterministic part, is revised with the newly available observation $\theta_o(k)$ of the present time step by using the EWMA model:

$$\overline{D}_{tod(k)} := \overline{D}_{tod(k)} + \lambda\left(\theta_o(k) - \overline{D}_{tod(k)}\right) \qquad (10)$$

where ":=" indicates that the evaluated result of the right-hand side is assigned to the left-hand side variable. Here, $tod(t)$ is the hour of day for time t. The exponential smoothing constant λ determines how the past observations are smoothed or averaged, and a value of 0.033 is used in this study. The stochastic part is derived by subtracting the deterministic part from the observation series:

$$S(t) = \theta_o(t) - \overline{D}_{tod(t)} \quad \left(t = k^* - 24d'+1, k^* - 24d'+2, ..., k^*\right) \qquad (11)$$

where d' denotes the number of days required for evaluating the AR parameters; it is set to 30 day in this paper. The parameters are estimated by the least squares method in which the one-step-ahead prediction errors of $24d' - p$ data samples are minimized where p is the order of the identified AR model. The temperature is then predicted by combining the deterministic and stochastic parts

$$\overline{\theta}_o(k^* + i) = \overline{S}(k^* + i) + \overline{D}_{tod(k^*+i)} \qquad (i = 1,2,..., L) \qquad (12)$$

where $\overline{S}$ is the prediction obtained from the AR model.

A preliminary study shows that the abovementioned DSM model tends to introduce a bias in the predicted temperature for longer lead times, such as 24 h, in intermediate seasons because the seasonal trend of the ambient temperature is steep in these seasons. Consequently, the yearly periodical variation is subtracted from the original data by fitting the Fourier series of the fifth order before applying the EWMA model (see Figure 2). The fitted data are the daily sampled temperatures in Tokyo derived by averaging the hourly data of 15 years (1981–1995) for each day of the year. After subtracting the yearly part, the EWMA and AR model are fitted. Equations (11) and (12) are revised as follows:

$$S(t) = \theta_o(t) - \overline{\theta}_{o,y,t} - \overline{D}_{tod(t)} \quad \left(t = k^* - 24d'+1, k^* - 24d'+2, ..., k^*\right) \qquad (13)$$

$$\overline{\theta}_o(k^* + i) = \overline{S}(k^* + i) + \overline{D}_{tod(k^*+i)} + \overline{\theta}_{o,y,k^*+i} \quad (i = 1,2,..., L) \qquad (14)$$

where $\overline{\theta}_{o,y,t}$ is the yearly periodical part for time t.

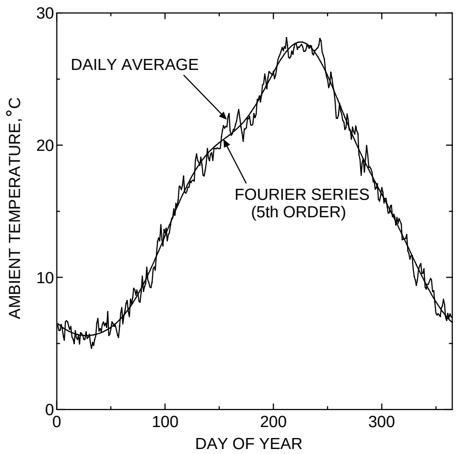

Figure 2. Yearly periodical temperature variation fitted with Fourier series

For the humidity ratio, the yearly periodical part is also subtracted first from the original series. However, the EWMA model is not applied because daily variation is not apparent. Therefore, instead of Equation (13), Equation (15) is used

$$S(t) = x_o(t) - \overline{x}_{o,y,t} \quad \left(t = k^* - 24d'+1, k^* - 24d'+2, ..., k^*\right) \qquad (15)$$

The subtraction of the deterministic part by only the yearly part leads to a deviation from the zero level for a considerably long period such as a few weeks. Hence, the mean is subtracted before fitting the AR model for humidity prediction:

$$S'(t) = S(t) - \tilde{S} \tag{16}$$

where $S'(t)$ is the series to which the AR model is fitted, and

$$\tilde{S} = \sum_{i=k^*-24d'+1}^{k^*} S(i) \Big/ 24d' \tag{17}$$

This operation produces the zero-mean time series, which is a basic requirement for fitting an AR model. The humidity ratio prediction is then provided by adding the following three parts: the prediction derived from the AR model, mean value represented in Equation (17), and the yearly periodical part $\bar{x}_{o,y,t}$.

For both temperature and humidity, the order of the AR model is assumed to be 2 in this paper.

Overviews of the results

Figure 3(a) shows a section of temperature prediction in case 2 in July. The initial prediction (chain line) is too low on July 11 and too high the next day due to a strong temperature fluctuation during these days. On the other hand, except on July 10, the corrected predictions at 6 p.m. (thin solid line) improve the initial predictions because the weather forecasts are more accurate than the initial predictions for the two days. On July 10, the weather forecast deviates from the realized values, and the improvement is not apparent. The corrected prediction profiles do not necessarily pass through the forecasted values because they take into account the reliability of the initial prediction to some extent. In particular, the corrected predictions at 10 a.m. (two-dot chain line) seem to almost ignore the weather forecasts. These results indicate the feature of the proposed method of determining prediction profiles by considering the balance of reliabilities between initial predictions and weather forecasts.

Figure 3(b) shows the humidity prediction results. The initial predictions resemble the prediction of a random walk model whose optimal prediction is the last observation value irrespective of the past observation history and prediction lead time. However, the presented initial prediction profiles exhibit a slight upward trend. This is because a prediction of an AR model decays to zero; this causes the humidity prediction to approach $\bar{x}_{o,y,t} + \tilde{S}$, which is approximately 14.6 g/kg (DA) during this period. Trial results show that the actual random walk model, which is fitted to $S(t)$ in Equation (15), produces higher prediction errors, particularly for long lead time.

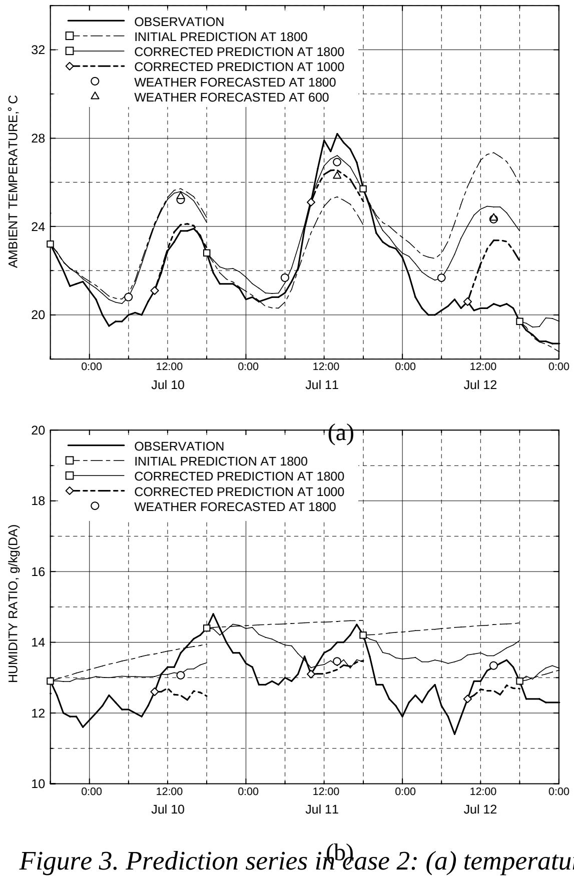

Figure 3. Prediction series in case 2: (a) temperature and (b) humidity ratio

Figure 4 shows the root-mean-square error (RMSE) of the predictions of case 2 for 1990. The RMSE of the forecasts revised using Equation (9) is also presented. For both temperature and humidity, the corrections made at 6 p.m. decrease the RMSE in comparison with the initial predictions made at the same time, particularly for daytime of the following day. In comparison with the corrections made at 6 p.m., the corrections made at 2 a.m. improve the accuracy for the short lead time; however, this improvement is not apparent for longer lead times. These results indicate maximum temperature/minimum humidity forecasts exhibit relatively higher accuracy for the daytime as compared to the initial predictions made at night time. On the other hand, the predictions made at 10 a.m. decrease the RMSE for the afternoon because the initial predictions are more accurate than the forecasts made early morning at 6 a.m. As in the previous figure, these results show that the proposed method combines the initial prediction and forecasts by considering the relative accuracy.

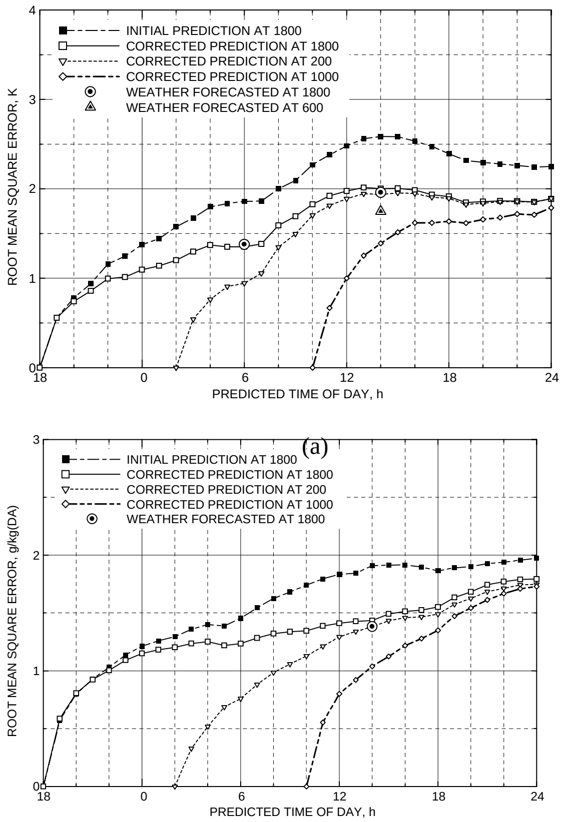

Figure 4. RMSE of predictions in case 2: (a) temperature and (b) humidity ratio

Case study results

Table 3 shows the RMSE of predictions for ambient temperature at 2 p.m. for each case. The RMSE of the revised forecasts of the maximum temperature are also listed. The introduction of updating for cases 3 and 4 provide poor accuracy for the predictions made at 2 a.m., RMSEs of which are higher than those made at 6 p.m. This suggests the occurrence of a malfunction because, theoretically, the prediction errors using the proposed updating method should decrease monotonically. The problem is studied in detail in the following section.

A shorter data storage period (case 5) is advantageous with regard to computational memory and load for estimating the elements of $\overline{\boldsymbol{P}}$, $\boldsymbol{R}$, and $\boldsymbol{S}$. The prediction errors are almost the same as those in case 2, but slightly larger. It is preferable to use relatively longer data storage periods such as two months for estimating these matrices.

The RMSE obtained in case 6 by neglecting correlations between the errors in the initial predictions and forecasts is almost the same as that in case 2, which considers the correlations. The following section describes additional studies in which the correlations vary.

Table 3. RMSE of predictions for ambient temperature at 2 p.m. (part 1), K

Case No.	Model Prediction made at			Forecast*2 Available at	
	6 a.m.*1	2 a.m.	10 a.m.	6 p.m.*1	6 a.m.
1	2.58	2.47	1.46	-	-
2	2.00	1.94	1.39	1.96	1.75
3	2.58	3.21	1.53	-	-
4	2.00	2.46	1.37	1.96	1.75
5	2.05	2.02	1.43	2.01	1.78
6	2.00	1.95	1.37	1.96	1.75

*1: Previous day
*2: Revised maximum temperature forecast derived using Equation (9) (data storage period for the parameter estimation is the same as that listed in Table 2)

VALIDATION WITH ARTIFICIALLY GENERATED DATA

In the previous section, it was shown that the proposed revision method provides poor accuracy for updating (cases 3 and 4). In this section, artificially generated observation and forecast data are used to validate updating again. The effect of the covariance $\boldsymbol{S}$ is also re-examined in this section.

Data generation

Instead of the real weather data, we use artificially generated data as observations. These data are generated using AR(2) model given by

$$x(t) = 1.42x(t-1) - 0.44x(t-2) + a_x(t) \tag{18}$$

The above parameters are determined with reference to the estimated values for the temperature prediction in the previous section. The standard deviation (SD) σ_x of random noise a_x is assumed to be 0.45, which is determined such that the SD of $\overline{x}_{14} - x_{14}$ obtained from Equation (18) is in close agreement with that obtained from the initial prediction results of the previous section, i.e., 2.58 [K] in Table 3. Here, x_{14} is the observed temperature at 2 p.m. and $\overline{x}_{14}$ is the initial prediction of temperature at 2 p.m. made at 6 p.m. on the previous day.

We also generate forecast data using the following model:

$$y_{14} = x_{14} + r_1\left\{r_2\left(\overline{x}_{14} - x_{14}\right) + \sqrt{1-r_2^2}\,a_y\right\} \tag{19}$$

where y_{14} is the forecasted value of temperature at 2 p.m. In this equation, x_{14} and $\overline{x}_{14}$ are both obtained by using Equation (18). a_y is random noise that is independent of a_x, and the SD is set to 2.58 [K], which is identical to the SD of $\overline{x}_{14} - x_{14}$. r_1 is ratio of SD of the forecast error $y_{14} - x_{14}$ to a_y, or $\overline{x}_{14} - x_{14}$. r_2 is the coefficient of the correlation between $y_{14} - x_{14}$ and $\overline{x}_{14} - x_{14}$. Because the SDs of both a_y

and $\bar{x}_{14} - x_{14}$, are the same, the SD of $r_2(\bar{x}_{14} - x_{14}) + \sqrt{1 - r_2^2}\, a_y$ remains unchanged regardless of the value of r_2. If r_2 is 0, no correlation exists between the initial prediction errors and forecast errors; this yields $\boldsymbol{S} = 0$.

Validation cases and results

The cases studied in this section are listed in Table 4. In the "Data Storage" column, "Batch" implies that $\bar{\boldsymbol{P}}$, $\boldsymbol{R}$, and $\boldsymbol{S}$ are estimated from the results of initial predictions and forecasts of two-year period calculation, which includes the validation period of one year (summary period of Table 5). In cases 12 and 13, the correlation r_2 between the initial prediction errors and the forecast errors is set to be greater as compared to those of the other cases where the correlation is set to the real correlation value derived in the previous section. The values of r_1 are set to 0.76 in all cases; this ratio is also derived from the results in the previous section.

Table 4. Cases studied for validation (part 2)

Case No.	Initial Prediction	Correction with Forecast	Data Storage	r_2	Covariance $\boldsymbol{S}$ *1
7	Every hour	Not corrected	60 days	0.68	C
8	6 p.m.	Not corrected	60days	0.68	C
9	6 p.m.	Not corrected	(Batch)	0.68	C
10	6 p.m.	6 p.m.	(Batch)	0.68	C
11	6 p.m.	6 p.m.	(Batch)	0.68	I
12	6 p.m.	6 p.m.	(Batch)	0.90	C
13	6 p.m.	6 p.m.	(Batch)	0.90	I

*1: C: Considered, I: Ignored

Table 5 shows a summary for the period of one year. In all cases, the RMSE decreases as time advances even when updating is introduced (cases 8 through 13). However, the RMSE in case 8 is higher than that in case 7 where updating is not introduced and an initial prediction is made every hour. As compared to Case 8, the revised estimation of $\bar{\boldsymbol{P}}$, $\boldsymbol{R}$, and $\boldsymbol{S}$ in case 9 improves the updating accuracy, and the RMSE is equivalent to case 7. This shows that updating is not inferior to repeating the initial prediction at every step in terms of accuracy under the condition that the summary period for estimating the matrices is sufficiently long enough, and the stochastic structures of observations and forecasts, such as the AR parameters or forecast accuracy, are time invariant. However, in reality, the stochastic structures are considered to be time variant due to such as seasonal changes, and it is impractical to use such a long period for estimating the related matrices. For practical applications, it is preferable to repeat the initial prediction at every time step instead of using successive updates.

The accuracy obtained by forcing $\boldsymbol{S}$ to 0 (case 11) is less than that obtained when $\boldsymbol{S}$ is estimated from the past results (case 10). This shows that the correction made by considering the correlations is superior when the stochastic structures (variance and covariance) are correctly estimated. The results of cases 12 and 13 show that the RMSE is apparently degraded when the correlation (r_2 is 0.9 in these cases) is ignored. The effect of considering $\boldsymbol{S}$ depends on the level of the correlations. Systematic studies using various regional weather data are needed to arrive at a conclusion whether the correlations should be considered.

Table 5. RMSE of predictions for ambient temperature at 2 p.m. (part 2), K

Case No.	Model Prediction Made at			Forecast Available at 6 p.m.*1
	6 p.m.*1	2 a.m.	10 a.m.	
7	2.50	2.21	1.30	-
8	2.50	2.43	1.51	-
9	2.50	2.18	1.27	-
10	1.87	1.71	1.17	1.88
11	1.92	1.78	1.20	1.88
12	1.79	1.65	1.15	1.88
13	2.05	1.89	1.24	1.88

*1: Previous day

CONCLUSIONS

This paper proposes a method for revising the prior predictions of ambient temperature and humidity by combining two additionally available different data sources, i.e., observations at the building site and forecasts from a weather station. It accepts any initial prediction method that is employed at the beginning of a prediction set.

Case studies using the one-year data of Tokyo, Japan show that in comparison with the initial predictions made from only observations, corrections with weather forecasts decrease the RMSE of the prediction made at night for the following daytime by approximately 0.5 K for temperature and 0.5 g/kg (DA) for humidity. However, the decrease in the RMSE for a short lead time are negligible. Incorporating additional observations from the night to early morning into the former prediction exhibits considerable improvement for the short lead time. Therefore, the proposed method decreases the RMSE of the prediction for a wide range of lead times by combining the two different data sources.

The validation test results also show that the accuracy obtained by repeated updating with consecutive observations is less than that obtained by making the initial prediction at every step. In order to overcome this problem, an extremely large data storage period such as one or two years should be maintained to correctly estimate the covariance matrices required for the updating. For practical applications, it is preferable to make initial prediction in each step, instead of the updating repetitions.

The proposed method for revising the former predictions is considered to have general versatility because it is not derived by a trial-and-error approach dependent on the site-specific weather. However, further validations using various regional data and various initial prediction methods are required to confirm the versatility of the proposed method.

NOMENCLATURE

k^* : time origin for initial prediction
k : current time
t : time
L : maximum lead time of initial prediction
$\boldsymbol{x}$: estimated vector (temperature and humidity)
$\boldsymbol{y}$: additional information vector (observation or forecast)
$\boldsymbol{v}$: noise vector included in $\boldsymbol{y}$ (observation or forecast error)
$\boldsymbol{P}$: covariance matrix of estimation errors of $\boldsymbol{x}$
$\boldsymbol{R}$: covariance matrix of $\boldsymbol{v}$ (covariance matrix of forecast errors)
$\boldsymbol{S}$: matrix representing the covariance between initial prediction errors and forecast errors
d : number of days for estimating $\overline{\boldsymbol{P}}$, $\boldsymbol{R}$, and $\boldsymbol{S}$
d' : number of days for estimating AR parameters
δ_i : condition flag whose value is 0 for $i \le L$ and 1 for $i > L$
θ_o : ambient temperature
x_o : ambient humidity ratio
$\theta_{o,\min}$: forecasted minimum ambient temperature
$\theta_{o,\max}$: forecasted maximum ambient temperature
$x_{o,\min}$: forecasted minimum ambient humidity ratio
$l(i)$: index representing nonzero column of the i th row of the coefficient matrix $\boldsymbol{H}$ in Equation (A-1)
$E[\bullet]$: expectation of random variable of $\bullet$

Superscripts

$\sim$: average
$-$: average or expectation, particularly an *a priori* estimate
$\wedge$: revised (*a posteriori*) estimate

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APPENDIX—MEASUREMENT UPDATE EQUATIONS OF THE KALMAN FILTER

The original Kalman filter (Kalman 1960) is a mixed procedure of time update and measurement update. The measurement update equations listed below are derived from decomposing the original procedure into the two updates (see Luenberger 1969 for example).
A measurement is assumed to be of the form

$$\boldsymbol{y} = \boldsymbol{Hx} + \boldsymbol{v} \tag{A-1}$$

In other words, the measurement $\boldsymbol{y}$ is assumed to be represented as a linear combination of states denoted by a vector $\boldsymbol{x}$ plus a random measurement error $\boldsymbol{v}$ whose expectation is zero and covariance is

$$\boldsymbol{R} = E[\boldsymbol{v} \cdot \boldsymbol{v}^T] \tag{A-2}$$

Let the *a priori* estimate of the state be $\overline{\boldsymbol{x}}$ and the covariance be

$$\overline{\boldsymbol{P}} = E[(\boldsymbol{x} - \overline{\boldsymbol{x}}) \cdot (\boldsymbol{x} - \overline{\boldsymbol{x}})^T] \tag{A-3}$$

Then, when an additional measurement $\boldsymbol{y}$ of the form of Equation (A-1) is available, the *a posteriori* minimum-variance estimate of the state is derived from

$$\hat{\boldsymbol{x}} = \overline{\boldsymbol{x}} + \boldsymbol{K}(\boldsymbol{y} - \boldsymbol{H}\overline{\boldsymbol{x}}) \tag{A-4}$$

and its covariance from

$$\hat{\boldsymbol{P}} = \overline{\boldsymbol{P}} - \boldsymbol{K}(\boldsymbol{HP} + \boldsymbol{S}^T) \tag{A-5}$$

where

$$\boldsymbol{K} = (\overline{\boldsymbol{P}}\boldsymbol{H}^T + \boldsymbol{S})(\boldsymbol{H}\overline{\boldsymbol{P}}\boldsymbol{H}^T + \boldsymbol{HS} + \boldsymbol{S}^T\boldsymbol{H}^T + \boldsymbol{R})^{-1} \tag{A-6}$$

$$\boldsymbol{S} = E[(\boldsymbol{x} - \overline{\boldsymbol{x}})\boldsymbol{v}^T] \tag{A-7}$$

The covariance $\boldsymbol{S}$ is often assumed to be zero or ignored.