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Multistage-Type Prediction System of Solar Radiation Using Simplified Fuzzy Reasoning Based on Weather Forecast and MSM-GPV

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Abstract

We describe a prediction system for solar radiation using simplified fuzzy reasoning based on weather forecasts and the mesoscale spectral model grid point value (MSM-GPV). The proposed prediction system has a multistage-type structure that consists of two parts: a function approximation part using a normal distribution function and a correction part using the simplified fuzzy reasoning. The output of the prediction system is hourly averages of predicted solar radiation from 6:00 to 18:00. Using solar radiation data acquired in the past, a self-tuning algorithm tunes fuzzy correction rules so that the prediction error is decreased. Several simulation results confirm the usefulness of the proposed prediction system.

1. Introduction

It is well known that solar radiation is one of the factors influencing crop growth. In order to harvest high-quality crops (e.g., with sufficient size or high sugar index) stably, it is very important to control the amount of irrigation so that the water stress of crops is maintained at a reasonable level regardless of changes in solar radiation. To meet this demand, we consider the control of an automatic irrigation system (AIS) on the basis of predicted solar radiation. By making the best use of predicted solar radiation, the AIS will be able to supply liquid fertilizer and/or water to crops in proper quantities. Therefore, this paper is focused on the solar radiation prediction system.

Until now, as research related to the prediction method of solar radiation, Orita et al. proposed the solar radiation system comprising a multistage neural network[1]. Kemmoku et al. proposed a method of predicting solar radiation using an artificial neural network[2]. These systems employ the observed pressure data. Therefore, meteorological equipment for obtaining pressure data is needed. Shimada and Kurokawa proposed a solar radiation prediction method for a photovoltaic system using weather forecasts and weather change patterns to improve the prediction accuracy[3]. Oke et al. proposed a forecasting-error reduction method of daily total insolation by integration of the forecasted daily solar ir-

radiance curve[4]. On the other hand, we proposed a simple prediction system using the approximated function based on weather forecasts and image of the sky observed with a camera. However, prediction error may be related to the accuracy of weather forecasts, and a long-term prediction is difficult owing to the drastic variation of the image of the sky[5]. As other method, we proposed the fuzzy prediction system of solar radiation using the mesoscale spectral model grid point value (MSM-GPV)[6]. Although this system can give long-term prediction, there is a limitation to the improvement the prediction accuracy.

In this paper, we propose a new prediction method combined with the two conventional prediction systems mentioned above[5, 6], the multistage prediction system of solar radiation using simplified fuzzy reasoning based on weather forecasts and MSM-GPV. This system has the possibility to predict the amount of solar radiation considering the changes in weather condition every hour, and the improvement of the prediction accuracy is expected. Computer simulations confirm the usefulness of the proposed prediction system.

2. Prediction System of Solar Radiation

2.1 Configuration of overall system

Figure 1 shows the configuration of the proposed prediction system of solar radiation using simplified fuzzy reasoning based on weather forecasts and MSM-GPV. The prediction process of this system is a multistage type consisting of two parts. One is the function approximation part to roughly estimate the daily solar radiation curve, and the other is the correction part to adjust the predicted solar radiation using MSM-GPV.

Input information of this system is weather forecasts provided by the Japan Meteorological Agency (JMA), prediction date, and the relative humidity data of MSM-GPV. The output is the predicted solar radiation $\tilde{I}(n)$. Here, the prediction term is set from 6:00 ($n=0$) to 18:00 ($n=12$). In Figure 1, we show that the prediction system was divided hourly to improve the prediction accuracy.

Figure 1: Configuration of proposed solar radiation prediction system

2.2 Approximation function

As seen in some solar radiation data, the daily solar radiation curve has a tendency to increase from sunrise, reach a peak during the day, and decrease toward sunset. That is, the daily solar radiation curve is similar to the shape of a normal distribution function. Therefore, we consider approximating the daily solar radiation curve using the normal distribution function as follows:

$$\hat{I}(t) = I_{\max} \exp \left\{ \frac{-(t - \tau)^2}{2\sigma^2} \right\} \quad (1)$$

where $\hat{I}(t)$ is the approximated daily solar radiation curve. τ and σ are the average and the standard deviation defined as

$$\tau = \frac{t_o + t_i}{2} \quad (2)$$

$$\sigma = \frac{t_i - t_o}{6} \quad (3)$$

where t_o and t_i are the sunrise time and the sunset time, respectively. $I_{\max}$ is the maximum value of the daily solar radiation calculated using the daily clearness indexes W represented in Table 1.

$$I_{\max} = \frac{10^6 \pi W I_o}{7200(t_i - t_o - 1)} \quad (4)$$

Here, I_o is the integration of the intensity of solar radiation $I(t)$ and is obtained from the theoretical formula for the prediction day[6].

Table 1: Clearness indexes

Weather forecasts	Clearness index W
Sunny	0.733
Cloudy	0.464
Rainy	0.099

The clearness index W shown in Table 1 is very convenient for treating weather forecasts quantitatively.

2.3 Correction part using simplified fuzzy reasoning

In the approximation function part, the daily solar radiation curve can be estimated. However, since the actual daily solar radiation frequently changes with weather conditions, there is a limit in the ability to improve the prediction accuracy using only Eq. (1).

We propose a correction method of using simplified fuzzy reasoning. As the input information of simplified fuzzy reasoning, we choose the relative humidity data of MSM-GPV provided at intervals of three hours up to fifteen hours ahead. As shown in Figure 2, the distance between each forecast point on the mesh is 5 km, and the forecasted relative humidity data show the value in a 5×5 km range including a lattice point. Therefore, we use the forecasted humidity data in the nearest forecasted grid mesh as input data of fuzzy reasoning. The solar radiation estimated using Eq. (1) and the relative humidity data of MSM-GPV are input to the fuzzy reasoning engine to correct the solar radiation $\hat{I}(t)$ estimated using Eq. (1), and the predicted solar radiation $\tilde{I}(t)$ is output.

Figure 2: Location of predicted and forecasted points

Generally, a fuzzy reasoning algorithm has the ability to estimate certain information from uncertain information by applying tuned fuzzy rules. In this paper, we focus on these features and introduce the simplified fuzzy reasoning engine in the proposed prediction system.

The fuzzy reasoning procedure is briefly described as follows. Input variables to the simplified fuzzy reasoning engine are the relative humidity data of MSM-GPV and the solar radiation estimated using the normal distribution function. These input variables are converted into suitable linguistic variables that may be viewed as labels of fuzzy sets. In this paper, the following five linguistic variables are used: minimum (MIN), small (SML), middle (MID), big (BIG), and maximum (MAX). Fuzzy sets corresponding to each linguistic variable are defined by assigning the grade of triangular membership functions shown in Fig. 3. For instance, two fuzzy sets are selected for input variables ($\hat{I}(t)$, $H(t)$), and

two grades μ_i and μ_j ($i, j=0\sim4$) are decided. As a result, four fuzzy rules are selected, as shown in Table 3. The grade of the selected fuzzy rule μ_{ij} is given by

$$\mu_{ij}(n) = \mu_i(n) \cdot \mu_j(n) \quad (5)$$

The output of the fuzzy reasoning engine $\tilde{I}$, that is, the predicted solar radiation, is obtained by

$$\tilde{I}(n) = \frac{\sum \mu_{ij}(n) \cdot W_{ij}(n)}{\sum \mu_{ij}(n)} \quad (6)$$

where $W_{ij}(n)$ is the tuning parameter of the selected rule and is adjusted by the following tuning law.

$$W_{ij}(n) = \gamma e_f(n) \mu_{ij}(n) + W_{ij}(n-1) \quad (7)$$

Here, $\gamma > 0$ is a positive tuning gain and $e_f(n) = I(n) - \tilde{I}(n)$ is the tuning error.

Figure 3: Membership functions

Table 2: Fuzzy rules

$\tilde{I}(n) \backslash H(n)$	MIN	SML	MID	BIG	MAX
MIN	W_{00}	W_{01}	W_{02}	W_{03}	W_{04}
SML	W_{10}	W_{11}	W_{12}	W_{13}	W_{14}
MID	W_{20}	W_{21}	W_{22}	W_{23}	W_{24}
BIG	W_{30}	W_{31}	W_{32}	W_{33}	W_{34}
MAX	W_{40}	W_{41}	W_{42}	W_{43}	W_{44}

3. Prediction Results of Solar Radiation

To confirm the usefulness of the proposed prediction system of solar radiation, we choose Ishii-cho, Tokushima City, Japan, as the prediction site. Computer simulation to predict

one-hour averages of solar radiation from 6:00 am to 6:00 pm for the year from January 2009 to December 2009 is carried out. Here, note that the observed solar radiation data (one year from January 2008 to December 2008) used for tuning fuzzy rules are not included in the above prediction period.

Figures 4(a)~4(d) show the simulation results of the daily solar radiation curve extracted from all results. In addition, to clarify the effect of the correction using the simplified fuzzy reasoning, observed solar radiation, approximated solar radiation using the normal distribution function based on weather forecasts, and the solar radiation predicted by the proposed system shown in Fig. 1. From these results, we can confirm that the proposed system grasps the rough transition of solar radiation and has a good correction effect. However, since the prediction error in July is large compared with other months, it is necessary to improve the prediction accuracy in summer.

To evaluate the prediction accuracy carefully, we use root mean square error (RMSE) in Eq. (8) and a correlation coefficient (COC) in Eq. (9).

$$RMSE = \sqrt{\frac{\sum_{n=1}^N \{I(n) - \tilde{I}(n)\}^2}{N}} \quad (8)$$

$$COC = \frac{\sum_{n=1}^N \{I(n) - \overline{I(n)}\} \{\tilde{I}(n) - \overline{\tilde{I}(n)}\}}{\sqrt{\sum_{n=1}^N \{I(n) - \overline{I(n)}\}^2 \sum_{n=1}^N \{\tilde{I}(n) - \overline{\tilde{I}(n)}\}^2}} \quad (9)$$

$I(n)$ is the observed solar radiation. $\tilde{I}(n)$ is the predicted solar radiation. $\overline{I(n)}$ and $\overline{\tilde{I}(n)}$ are the averages of $I(n)$ and $\tilde{I}(n)$, respectively. n is the data counter. N is the number of total data.

Table 3 shows the RMSE and COC for each month in 2009. From this result, it can be seen that the RMSE has a tendency to increase in the spring and summer periods and to decrease in the autumn and winter periods. On the other hand, since the correlation coefficients COC for all months is more than 0.83, there is a strong correlation between the observed and predicted solar radiation curves. That is, it is apparent that the proposed two-stage prediction method that comprises a combination of the rough estimation process using a function approximation technique and the correction process using the simplified fuzzy reasoning technique with predicted weather conditions is valid.

4. Conclusions

In this paper, we proposed the multistage solar radiation prediction system, and showed that it is possible to predict

Table 3: Prediction results

Month	RMSE	COC	Month	RMSE	COC
Jan.	86.5	0.90	Jun.	147.7	0.83
Feb.	106.2	0.87	Aug.	135.7	0.89
Mar.	126.1	0.88	Sep.	121.1	0.91
Apr.	133.1	0.90	Oct.	90.3	0.93
May	137.4	0.89	Nov.	98.3	0.88
June	142.5	0.88	Dec.	81.8	0.90

Figure 4: Prediction results of daily solar radiation curve

long-term solar radiation using weather forecasts and MSM-GPV. To evaluate the prediction accuracy of the proposed prediction system, we used the RMSE and the correlation coefficient. As a result, we could confirm the effectiveness of the proposed multistage prediction system for improving the prediction accuracy. However, the prediction accuracy in summer was unsatisfactory compared with other seasons.

Future works will focus on improving the prediction accuracy in summer by choosing effective input data for each month, and on applying the proposed solar radiation prediction system to the automatic irrigation system for cultivation in plastic greenhouses.

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