Simple model for predicting hourly air temperatures inside Chinese solar greenhouses

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Abstract: For an efficient energy greenhouse, temperature is the most important climate parameter, which not only affects crop growth and health but also determines the management of energy consumption. So reliable monitoring of temperature is of great significance, and often hourly values are required. However, due to the low level of automation for Chinese solar greenhouse, the loss or poor quality of climate data often occurs. In order to accurately supplement the missing data, as well as for the generation of future temperature, a 24-hour indoor temperature prediction model was established. It uses a piecewise Bezier curve equation that takes the characteristic temperature as the control point which was determined by the outside weather recording. The 130 d of observed hourly temperature data were used to build and validate the model, and the results showed that the temperature model proposed was accurate and sufficient for the simulation of the trend curve of hourly temperature change inside a solar greenhouse. (EF=0.98, R^2=0.89). After validation, this temperature model proposed can be useful for the quantitative analysis of crop growth and optimal management.

Keywords: solar greenhouse, hourly temperature, prediction model, Bezier curve equation

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1 Introduction

Solar greenhouse is the main facility type of vegetable production in northern China. Compared with the closed modern greenhouse, a solar greenhouse is a semi-open system in which climate is more affected by manual intervention and local weather[1]. The continuous and short-time scale monitoring of the environment is of great significance for scientific research and engineering applications inside the solar greenhouse[2]. On one hand, it can help to explore the experience of farmers' planting management mode. On the other hand, it provides the required climate factors for the quantitative analysis of crop growth and optimal resource management[3-6].

The greenhouse environmental variables are monitored by low-cost sensors whose values are collected by the remote data logger. Due to the lack of regular maintenance of types of equipment or occasionally power and network failure, poor quality data collection often occurs causing missing or incorrect climate information. However, for further research on crop production inside solar greenhouses, it is necessary to explore a method or a model to approximate the missing climate data. With the integrity of the greenhouse environment for a long time, the analysis uncertainty of crop growth related to climate could be largely reduced, which will further promote the development of the environmental model and crop growth model[7-9].

Temperature is a principal element inside a solar greenhouse, which not only affects crop growth and health[10,11] but also determines the management of energy consumption. Compared with other environmental variables such as radiation and CO_2 measurement, the temperature sensor is more accurate and stable, but temperature distribution and changing patterns are subject to greenhouse type and local weather[12]. Many scholars have studied the temperature model inside the greenhouse for different research purposes, for instance, to model temperature distribution or to locate the sensor's position[13-16]. The objective of this paper is to explore a method or a model to approximate the vacant data as accurately as possible, and meanwhile to provide a simulation tool of internal temperature forecasts for Chinese solar greenhouse. Considering that the model will be deployed in the embedded edge computing terminal, the complexity of the model should not be too high. Therefore a simple and valid modeling method will be studied, meeting both the requirements of accuracy and easy implementation[17-19].

2 Materials and methods

2.1 Field experiment

Experimental research was carried out in the solar greenhouse located in the Zhuozhou experimental field of China Agricultural University (latitude and longitude: lat.39.906o, long.116.407o). The overall span of the greenhouse is 6.5 m, and the ridge height is 3.0 m. The projection of the south slope and the north slope is 5.2 m and 0.8 m respectively, and the north wall is 2.3 m high. The arc part was covered with polyethylene foil with a thickness of about 0.10-0.15 mm. The total planting area of the greenhouse is about 357.5 m^2.

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Cucumber is cultivated in greenhouse, and horticultural management strategies are conducted according to the long-term accumulated experience of farmers. Temperature, humidity, radiation, and CO_2 were recorded every 10 min by a commercial data logger (Zhongnong Jinwang (Beijing) Agricultural Engineering Technology Co., Ltd.). The climate inside the greenhouse was not controlled. During the experiments, the position of sensors for measuring the internal temperature was carefully selected. A calibrated hand-held sensor was used to measure the temperature of different positions in the experimental greenhouse. Through the analysis, the sensor was placed in the middle of the greenhouse, 3.5 m from the north wall and 2.2 m from the ground (Figure 1), where the observation temperature is closest to the average one.

Note: Circle in red indicates the installation position of the temperature sensor.

Figure 1　Installation position of temperature sensor inside the experimental greenhouse

The accuracy of the temperature sensor is ±0.5°C, with a measurement range is −40°C-120°C (HSTL 102w), and the humidity measurement accuracy is ±4.5% RH, ranging from 0%-100%, (HSTL 102s). The accuracy of the light sensor adopted is ±7% accuracy and its measurement range is 0-10 000 lx (HSTL-GZD). The outdoor meteorological data are from the weather station (station id: chm00054511, Beijing), including daily average temperature, maximum temperature, minimum temperature, and precipitation information.

2.2　Data preprocessing

Important for the merits of the obtained data sets is their reliability. The accuracy of temperature measurement was estimated by error analysis. When abrupt change is detected, it most likely means that a measurement error occurs either due to interfered transmission or the sensor fault. To solve the abnormal case described above, the 3σ rule was adopted using Equation (1)[20].

$$\left|X_n-\bar{X}\right|>3\sigma,\ X'_n=(X_{n-1}+X_{n+1})/2 \qquad (1)$$

where, σ is the standard deviation of the temperature data series; X_n is the real value; X'_n is the data value after abnormal processing; $\bar{X}$ is the mean value of the data series. If the absolute value of the difference between the detected value and the average value of the series exceeds three times the standard deviation, the data is regarded as abnormal data. When detecting such data, it is necessary to replace it with the average values around the neighborhood period of the abnormal point.

2.3　Model description

Data obtained from measurements were analyzed by R language (R Core Team (2019). https://www.R-project.org/.) and prepared for the model creation. The data from 130 dates over the 2017 and 2018 spring was used to make an analysis and evaluate the model.

From measurements of the temperature inside the greenhouse, it was found that the variation of hourly temperature throughout the day follows a smooth curve whose shape can be regulated by control points and their values. The piecewise quadratic Bezier curve is flexible enough to represent the above characteristics. So the mathematical equation of the Bezier curve was used to model the trend curve of hourly temperature inside the greenhouse. The revised equation is described as follows:

$$B(t)=(1-a)^2P_0+2a(1-a)P_1+a^2P_2,\ a\in[0,1] \qquad (2)$$

where, t is an integer ranging from 1 to 24; a is the parameter which can be adjusted by trial; $B(t)$ is used to calculate the value of temperature at the time t and the control points P_0, P_1, and P_2 will ensure smooth transition for each moment. The values of P_0, P_1, and P_2 are closely related to internal temperature, i.e., average T_{mean}, maximum T_{max}, and minimum T_{min}.

According to the variation of temperature for 24 h inside the greenhouse, the Bezier curve model subjected to four-time segments was built and listed in Table 1.

Table 1　Piecewise Bezier curve model for internal temperature of day-time (24 h)

Time	Model description	Values of control points	Values of parameter
5:00-8:00	$H(5)=T_{min}$ $H(t)=(1-a)^2P_0+2a(1-a)P_1+a^2P_2$; $t=6,7,8$	$P_0=T_{min}$ $P_1=P_2=T_{mean}$	$a=\left[\frac{1}{6},\ \frac{2}{6},\ 1\right]$
9:00-14:00	$H(t)=(1-a)^2P_0+2a(1-a)P_1+a^2P_2$; $t=9,10,11,12,13,14$	$P_0=T_{min}$ $P_1=P_2=T_{max}$	$a=\left[\frac{1}{6},\ \frac{2}{6},\ \frac{3}{6},\ \frac{4}{6},\ \frac{5}{6},\ 1\right]$
15:00-19:00	$H(t)=(1-a)^2P_0+2a(1-a)P_1+a^2P_2$; $t=15,16,17,18,19$	$P_0=P_1=T_{max}$ $P_2=T_{mean}$	$a=\left[\frac{1}{6},\ \frac{2}{6},\ \frac{3}{6},\ \frac{4}{6},\ 1\right]$
20:00-5:00	$H(t)=(1-a)^2P_0+2a(1-a)P_1+a^2P_2$; $t=20,21,22,23,24,1,2,3,4,5$	$P_0=P_1=T_{mean}$ $P_2=T_{min}$	$a=\left[\frac{10}{20},\ \frac{11}{20},\ \frac{12}{20},\ \frac{13}{20},\ \frac{14}{20},\ \frac{15}{20},\ \frac{16}{20},\ \frac{17}{20},\ \frac{18}{20},\ 1\right]$

3　Results

In Figure 1, the measurement of temperature in the greenhouse and outside the greenhouse are shown from April to June of the year 2017 and 2018, during which period, the measurement of corresponding date was daily averaged. From the comparison, internal temperature fluctuation is more gentle than outside one, and in the early spring of northern China, the temperature inside solar greenhouse is higher than outside temperature, but with the increase of temperature in summer, the indoor temperature begins to be lower than the outdoor temperature, which might be affected by the structure of solar greenhouse and manual operation on shading, heat insulation and ventilation device by the farmer. However, we can still conclude from the curve that there is a strong correlation between indoor and outdoor average temperatures (Figure 2). Note that the higher the outdoor temperature, the smaller the indoor and outdoor temperature difference is (Figure 3). These results could explain that the inside temperature of a solar greenhouse mainly depends on the natural ventilation and the sun's radiation and no automatic control of temperature is conducted according to fixed set points.

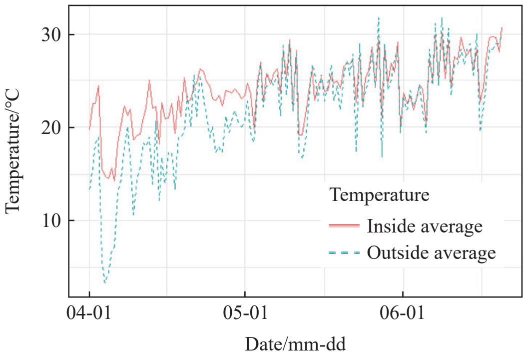


Figure 2 Comparison of average temperature trend of the year 2017-2018 inside and outside the greenhouse

In addition to the average temperature, the daily minimum temperature and maximum temperature were also key input parameters for the Bezier curve model. So regression analysis was also carried out to evaluate the relationship between internal extreme temperatures and outside ones. In Figure 4 the trend of indoor and outdoor maximum temperature, average temperature, and minimum temperature were shown and compared in one graph. It can be concluded that indoor average temperature, maximum temperature, and minimum temperature are basically consistent with the outdoor trend.

Through data analysis and statistical regression, two methods are presented in this paper to approximate the maximum and minimum indoor temperature which provides a different solution according to data loss condition. With known outside maximum or minimum temperature, we can use the linear relationship to approximately obtain the internal maximum or minimum

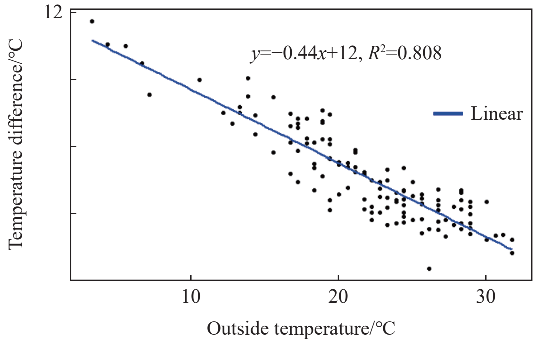


Figure 3 Daily average temperature difference versus outdoor temperature

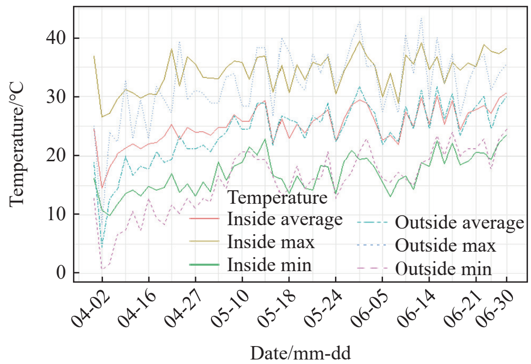
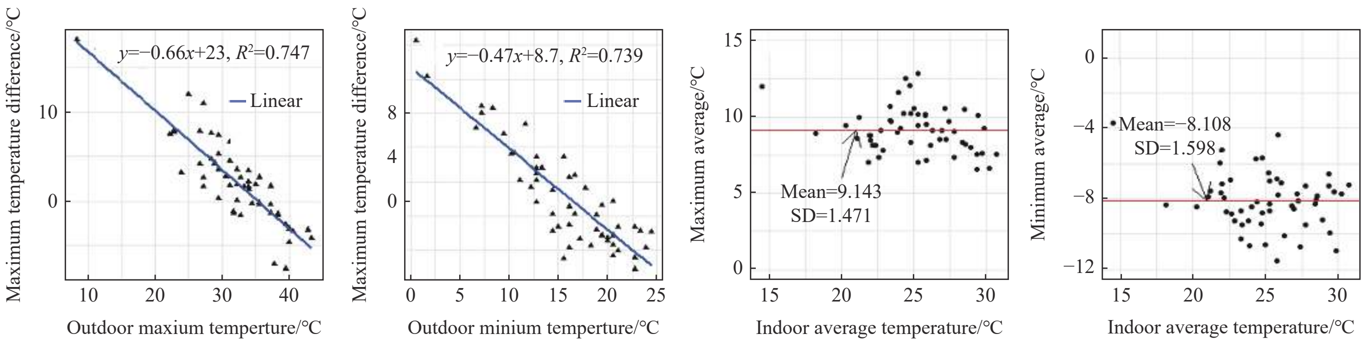


Figure 4 Comparison of variation trend of indoor and outdoor maximum temperature, average temperature, and minimum temperature

temperature(Figures 5a and 5b), while if only the average temperature is known from measurement, internal maximum, and minimum temperature can also be estimated by adding to or subtracting a constant from average one as shown in Figures 5c and 5d. The proposed methods to approximate the average, maximum, and minimum temperature provide the necessary values of control points in the model for the day when internal measurement is lost.



a. Outdoor maximum temperature b. Outdoor minimum temperature c. Indoor maximum temperature d. Indoor minimum temperature

Figure 5 Correlation Analysis of indoor and outdoor maximum and minimum temperatures

In order to establish an hourly time-scale temperature prediction model, the hourly measured average temperature data from different weather conditions were also analyzed, and Figure 6 shows the curve of temperature versus time of the day.

It can be seen from the curve the lowest temperature usually occurs around 5:00 in the morning no matter what season or weather conditions, while the highest value usually occurs around 14:00 at noon, which follows the results in the literature(Jun and Yu, 2015). The average temperature of every hour was also compared with the daily average temperature. According to statistical analysis of the difference between them shown in Figure 7,

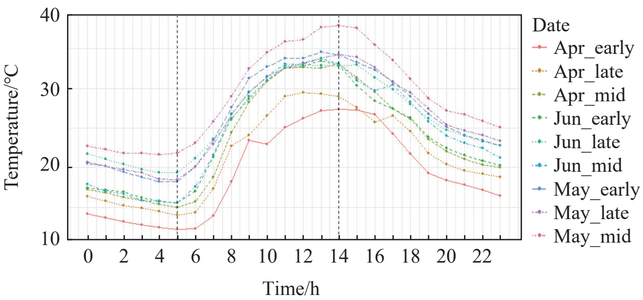
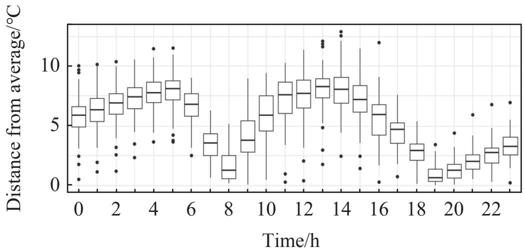


Figure 6 Variation trend of hourly temperature in Solar Greenhouse

it could be concluded that the temperatures at 8:00 and 19:00 are the closest to the daily average temperature in the greenhouse.

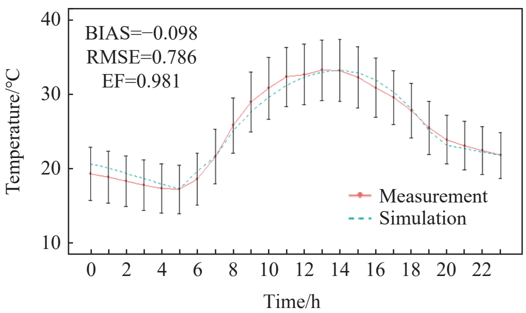


Note: Vertical bars indicate the standard error of mean.

Figure 7 Statistical analysis of the difference between hourly temperature and the daily average temperature in the solar greenhouse

Based on the above analysis of the correlation between indoor and outdoor maximum temperature, minimum temperature, and average temperature, we get the relationship between indoor average temperature and outdoor average temperature $y=-0.44x+12.00$, where x is the outdoor daily average temperature and y is the daily average temperature in the solar greenhouse; The relationship between the indoor maximum temperature and the outdoor maximum temperature is described as $y=-0.66x+23.00$, where x is the outdoor maximum temperature and y is the daily maximum temperature. The relationship between the indoor minimum temperature and the outdoor minimum temperature is $y=-0.47x+8.70$, where x is the outdoor daily minimum temperature and$y$is the solar greenhouse's daily minimum temperature. According to the statistical correlation relationship described above, when the internal temperature measurement is missing for some dates, their indoor average, maximum, and minimum values can be estimated according to the outdoor weather. With these parameters as input to the Bezier curve model, the temperature value for 24 hours a day could be approximated.

To investigate the model's ability to describe the greenhouse hourly temperature during the day, simulations were compared with measurements (Figure 8). The measurements shown as the red smooth curve in Figure 8 come from 15 to 20 May 2017 and were averaged as the observation value for every hour. The outside average and extreme temperature were input to the model and the dotted curve was shown as the simulation result. It can be seen that simulated temperature follows the dynamic trends in the measurements, though sometimes local over- and underestimation do occur due to simulation error.



Note: Vertical bars indicate the standard error of mean.

Figure 8 Comparison of 24 h temperature trend between observation and simulation

Further validation research was conducted and more data from March to June over the years of 2017 and 2018 were used to validate the model. The simulation results against measurement were made a comparison in Figure 9, and by linear regression, It can be seen that model simulation agreed well with observed values (EF=0.98, R^2=0.89).

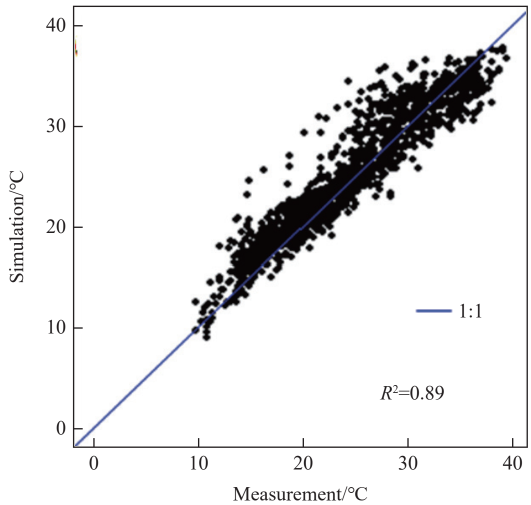


Figure 9 Simulated temperature plotted against measurement for 1801 h data from March to June over the years of 2017 and 2018

4 Conclusions and discussion

The model of the piecewise Bezier curve was able to simulate the hourly temperature of daytime (24 h) when only outside climate measurements were available. However, the model needs more measurements from different seasons and years to be analyzed so that the relations observed are not limited to the experiments described in this study, or have a more general value. Although the simulated trend curve is reasonable, the accuracy of a single value still needs to be improved, and the model did not take into account the other climate parameters, which may influence the accuracy of prediction. In addition, the selection of parameters also has an impact on the simulation accuracy of the model, so the adaptive method is needed to select the parameters to reduce the uncertainty brought by trial and error. Despite these shortcomings, the model is valuable. The mechanism of the model is clear and easy to implement. The results showed reasonable agreement between measured and simulated temperatures. It can be used as a supplementary tool to approximate the temperature variation inside a solar greenhouse. Combined with precipitation information from weather stations, it is likely to be used to calculate the average value of radiation entering into greenhouse and its variation. When validated, the model can be used as an environmental simulation tool to carry out systematic research about crop growth and greenhouse optimal management.

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