INVITED PAPER

Grain Pile Temperature Forecasting from Weather Factors: A Support Vector Regression Approach

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***Abstract*—Food storage security is critical to the national economy and people's lives. The environmental parameters of the granary should be accurately monitored in order to provide a better preservation environment for food storage. In this paper, we use temperature sensors to measure and collect grain temperature data for a period of 423 days from a real world granary, and collect the corresponding meteorological data from China Meteorological Data Network. We propose to leverage weather data to predict the average temperature of the grain pile with a support vector regression (SVR) approach. We first analyze the correlation between a large amount of historical data from the granary and the corresponding weather forecast data based on the Pearson correlation coefficient. In addition, we implement outlier detection and data normalization for data preprocessing. Finally, we incorporate different kernel functions in the SVR model to predict the temperature of grain pile using weather data. The results show that the proposed approach is highly accurate and the Gaussian radial basis function (RBF) kernel function achieves the best performance.**

***Index Terms*—Food storage; Temperature sensors; Weather metrics; Support Vector Regression; Machine learning.**

I. INTRODUCTION

The demand for food will be doubled by 2050 as population and social mobility increase [1]–[5]. Globally, more than 2 billion tons of food are harvested each year [6]. However, up to one third of the annual total global production of grain is lost because of poor post-harvest management. Lack of control over grain moisture content, high temperature, and insect infestation are the three most significant factors causing the loss. In fact, high grain moisture and temperature can provide favorable conditions for hot spot development, mold growth, and insect infestation [7]. Grain is still a physiologically active organism during storage, and is affected by the physical and biological environment. These internal and external factors are closely related to the safe storage of grain. With the development of science and technology, grain storage technology has been improved, and food security has been better guaranteed. However, there are still many risk factors in the process of grain storage; so green grain storage is particularly important. The complex grain storage ecosystem is under the joint influence of the environment sub-ecosystem and the granary protection construction [8].

Grain temperature is an important indicator of grain conditions. Its detection and control technology are critical for the operation of grain warehouses (or, granary). In the entire grain detection system, detection of the temperature of stored grain is a relatively mature technology and has been widely used in national reserves [9]. In fact, the storage temperature is highly predictable when aggregating over thousands of granaries and storage parameters. Different from the developed countries, the present situation of grain storage in China is unique [7]. Recently, Yang et al. present a non-destructive and economic wheat moisture detection system with commodity WiFi, which can achieve high classification accuracy for both LOS and NLOS scenarios [10], [11]. Many high-precision mathematical models and improved measurement systems are proposed to improve temperature monitoring and food storage management capabilities [12]–[14]. However, the work of grain temperature forecasting has been focused on time series models, which does not consider the effect of external weather factors. In fact, weather factors have been successfully utilized for accurate solar intensity forecasting [15], [16].

To improve the accuracy of grain pile temperature forecasting, we focus on the issue of using the National Meteorological Information Center (NMIC) weather forecast to accurately predict grain pile temperature. In this paper, we first discuss the temperate measurement system for food storage. For a period of 423 days, we used temperature sensors to measure and collect of grain temperature data from the grain storage at the *No. 1 Warehouse* in the Xishan District of Kunming, Yunnan province, China. We also collect the corresponding meteorological data from China Meteorological Data Network. We provide an analysis of the correlation between a large amount of historical data from the granary and the corresponding weather data. We find that the surface temperature of grain pile has higher correlations with air temperature, relative humidity, and 0cm ground temperature, but a smaller correlation with air pressure. We propose to predict surface temperature of grain pile using multiple weather factors, aiming to achieve high predication accuracy.

In particular, we develop a support vector regression (SVR) approach [17] to predict surface temperature of grain pile using multiple weather factors. In fact, because of some outliers recorded by temperature sensors, the raw data cannot be directly employed for the SVR model. We implement outlier detection and removal to delete bad data samples, and apply data normalization to all the sampled data to guarantee that the weather data and the surface temperature of grain pile have the same unit. Then, we leverage the calibrated meteorological data and grain temperature data to train the SVR model. Finally, we compare the prediction accuracy using different kernels, such as the linear kernel function, the polynomial kernel function, and the Gaussian radial basis function (RBF) kernel in the SVR model.

The main contributions of this paper are summarized below.

- To the best of our knowledge, this is the first work to use meteorological metrics to predict the average temperature of grain pile with an SVR approach.
- We employ temperature sensors to measure the grain temperature data from a real world grain storage for a period of 423 days, and the collect meteorological data for the same region and time period. Then, we analyze the correlation between a large amount of historical granary data and the corresponding weather data based on the Pearson correlation coefficient.
- We implement outlier detection and data normalization for the raw weather and grain pile temperature data. We use different kernel functions with the SVR model to predict the average temperature of grain pile based on meteorological data. We compare the accuracy of grain surface temperature prediction using different kernel functions. The results show that the Gaussian RBF kernel function achieves the best performance.

The remainder of this paper is organized as follows. The granary temperature measurement system is presented in Section II. Section III describes grain temperature data measurement, collection process, and data analysis. Section IV discusses data preprocessing and the SVR model. Section V validates the performance of the proposed method using real world data. Section VI summarizes this paper.

II. The Temperature Measurement System

To collect grain temperature data, we deploy a set of temperature sensors in the tall granary. Fig. 1 illustrates the tall flat granary architecture, which is divided into 10 rows from east to west, five regions from south to north, and four layers from top to bottom. Then 200 temperature sensors are deployed in this granary; the sensors are encapsulated in cables and the cables are inserted into the grain pile at certain places. In the tall square granary, the temperature sensor layout principle is that the distance between the horizontal and horizontal temperature measuring cables should be no more than 5 m, the distance between the vertical cables should be no more than 2 m, and distance from the cables to the grain surface, granary bottom, and granary wall should within 0.3 m to 0.5 m.

Fig. 2 presents a cross-sectional view of the granary. The temperature monitoring system generally includes temperature sensors, temperature measuring cables, and a computer monitoring terminal. Each vertical line in the figure represents a

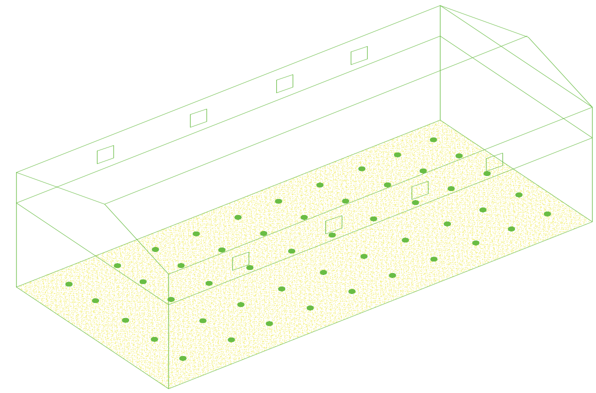


Fig. 1. The tall flat granary model.

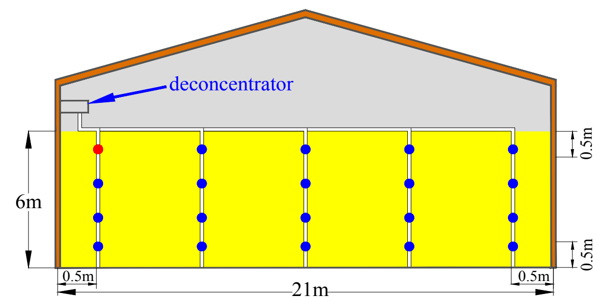


Fig. 2. The cross section view of a granary.

cable, and four temperature sensors are encapsulated in each cable. To monitor the abnormal change of temperature in the early stage of grain damage, the distance between the temperature measuring cables should be less than 0.5 m. Therefore, a large number of cables are needed, which would be hard to deploy (i.e., buried in the gain pile at precise locations) and lead to high measurement cost. Fig. 3 is the structural diagram of the grain condition measurement and control system in the granary. The computer sends test commands to the extension, receives test data from the extension, and then processes the receiving data. The extension receives the computer command, detects temperature data, and sends the results to the computer. The digital sensor is encapsulated inside the cable and laid inside the barn. Both digital temperature sensors and humidity sensors use a wire bus communication protocol to report sensory data.

The inspection time of grain temperature is preferably from 9 am to 10 am every day, when the temperature is close to the daily average temperature. While checking the temperature of the grain, we should also check the temperature inside the granary and the temperature outside the granary for analysis and comparison. All data is sampled once a day.

III. Data Collecting and Analysis

We measured and collected the grain temperature data of the grain storage in the *No. 1 Warehouse* at Xishan District of Kunming, Yunnan, China for a period of 423 days since January 1, 2017. Then we downloaded the meteorological data of the corresponding region for the corresponding period of time from

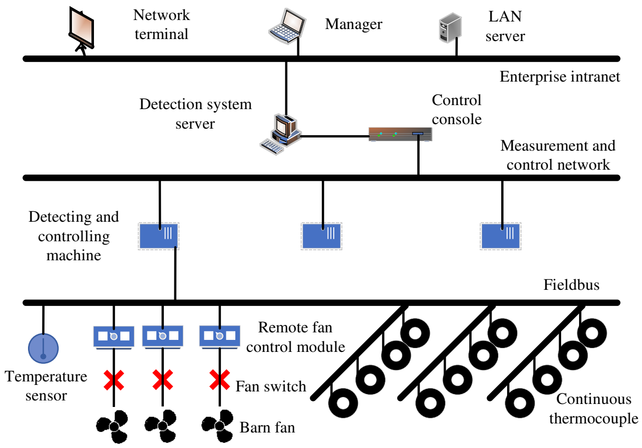


Fig. 3. Structure of the grain condition measurement and control system.

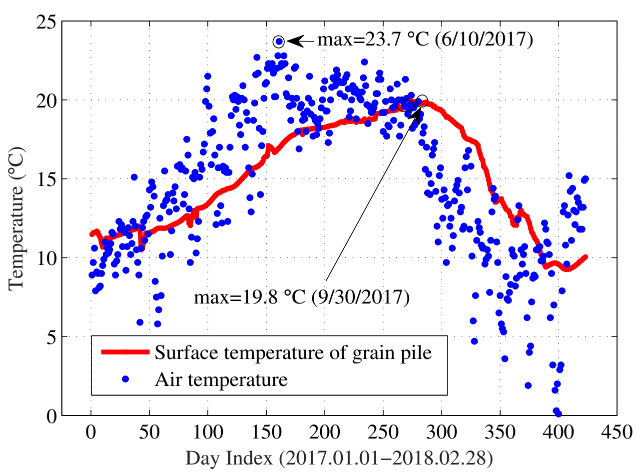


Fig. 4. Average temperature of the first layer of the stored grain pile and air temperature over days.

China Meteorological Data Network (http://data.cma.cn/). The weather metrics include air pressure, air temperature, relative humidity, precipitation, evaporation, wind speed, sunshine duration and 0 cm ground surface temperature. The temperature samples of grain pile are recorded by deployed sensors at 9 am every day. Then, we measure how the surface temperature of the grain pile changes with the weather variables and how these variables are influenced by each other.

Fig. 4 presents the surface temperature of the grain pile and the air temperature of the period. We find that the surface temperature of the grain pile and the air temperature are positively correlated. In other words, the temperature of the first layer of the stored grain pile becomes higher or smaller as the air temperature increases or decreases. However, there are other factors that also contribute to the surface temperature of the grain pile reading, since the surface temperature of the grain pile has been delayed for several months compared to the air temperature. It is noticed the highest air temperature was in June, while the highest temperature of the first layer of the grain pile was in September.

In Fig. 5, we can see that air temperature (subplot (a)), 0 cm ground surface temperature (subplot (b)), and relative humidity (subplot (c)) are all positively correlated with the surface temperature of the grain pile, especially at higher values. If the air temperature, 0 cm ground surface temperature, or relative humidity become larger, the surface temperature of the grain pile will likely increase too.

To study the correlation between the average temperature of the first layer of the stored grain pile and the weather metrics, we compute the Pearson correlation coefficients between pair of the factors. Table I provides the Pearson product moment correlation coefficients for all the weather variables and the surface temperature of grain pile. The higher the absolute value of the correlation coefficient, the higher the correlation between the two parameters. From Table I, we find that the surface temperature of grain pile has higher correlations with air temperature, relative humidity, 0 cm ground temperature, but with a smaller correlation with air pressure. Based on this study, we develop an SVR algorithm to predict the surface temperature of grain pile using multiple weather parameters, which is discussed in the following section.

IV. Prediction Model for Grain Pile Surface Temperature

In this section, SVR is utilized to predict the surface temperature of grain storage. Due to some outliers recorded by the sensors, the data units are inconsistent; thus the raw data cannot be directly used by the SVR model. Therefore, the data must be processed first before SVR predition. The data processing module includes outlier detection and data normalization, which are discussed in the following.

- *Outlier detection*: Some abnormal values are reported by temperature sensors. Outlier detection is used to recognize bad data values, which should be removed from the raw data. In this paper, we leverage the *Pauta criterion* method and the *linear trend at point* method to get rid of outliers. The outlier detection method is as follows.

Step 1: Let X_i, $i = 1, 2, ..., n$, be the ith value of weather metrics or the average temperature of the first layer of grain pile. We calculate the arithmetic mean value as

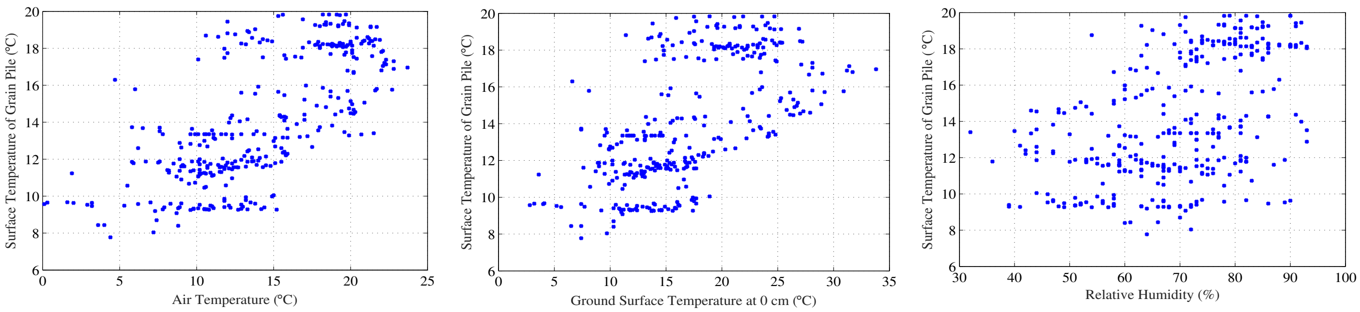
$$\bar{X} = \frac{1}{n} \sum_{i=1}^{n} X_i. \tag{1}$$

Step 2: We then obtain the residual e_i as in (2) and the standard deviation σ of the weather metrics or the average temperature of the first layer of grain pile as in (3).

$$e_i = X_i - \bar{X}, \quad i = 1, 2, ..., n \tag{2}$$

$$\sigma = \sqrt{\frac{1}{n-1} \sum_{i=1}^{n} (X_i - \bar{X})^2}. \tag{3}$$

Step 3: For all X_i, $i = 1, 2, ..., n$, if $|e_i| > 3\sigma$, we consider X_i as an abnormal value and replace it with the arithmetic mean value $\bar{X}$.



(a) Air temperature (b) 0cm ground surface temperature (c) Relative humidity

Fig. 5. Average temperature of the first layer of the stored grain pile generally increases with increased (a) air temperature, (b) 0 cm ground surface temperature, and (c) relative humidity.

TABLE I
CORRELATION MATRIX SHOWING CORRELATION BETWEEN DIFFERENT FORECAST PARAMETERS

	Airpre	Airtem	Relhum	Preci	Eva	Windspeed	Sunduration	0cmgrotem	graintem
Air pressure	1.000	-0.499	0.13	-0.119	-0.241	-0.099	-0.175	-0.436	-0.088
Air temperature	-0.499	1.000	-0.005	0.228	0.125	-0.070	0.135	0.953	0.706
Relative humidity	0.135	-0.005	1.000	0.394	-0.788	-0.633	-0.715	-0.091	0.494
Precipitation	-0.119	0.228	0.394	1.000	-0.215	-0.217	-0.403	0.152	0.350
Evaporation	-0.241	0.125	-0.788	-0.215	1.000	0.539	0.566	0.213	-0.339
Wind speed	-0.099	-0.070	-0.633	-0.217	0.539	1.000	0.362	-0.039	-0.396
Sunshine duration	-0.175	0.135	-0.715	-0.403	0.566	0.362	1.000	0.221	-0.260
0 cm ground temperature	-0.436	0.953	-0.091	0.152	0.213	-0.039	0.221	1.000	0.623
Surface temperature of grain pile	-0.088	0.706	0.494	0.350	-0.339	-0.396	-0.260	0.623	1.000

Step 4: Repeat the above three steps till all the X_is are processed.

- Data normalization: To guarantee that the weather data and the surface temperature of grain pile have the same unit, we choose the *zero-mean normalization* method to normalize all sampled data. The normalized value Z_i is computed as

$$Z_i = \frac{1}{\sigma} \cdot (X_i - \bar{X}),\ i = 1, 2, ..., n. \tag{4}$$

After data preprocessing, the training samples are

$$\mathcal{T} = \{(\mathbf{x}_1, y_1), (\mathbf{x}_2, y_2), ..., (\mathbf{x}_n, y_n)\}, \tag{5}$$

where $\mathbf{x}_i$ is a vector of eight calibrated meteorological metrics in the ith sample, and y_i represents the calibrated average surface temperature of grain pile in the ith sample. The SVR model is then utilized to learn a function $f(\mathbf{x})$, which is close to the gain surface temperature y as much as possible [17]. The function is defined by

$$f(\mathbf{x}) = \boldsymbol{w}^T \cdot \phi(\mathbf{x}) + b, \tag{6}$$

where $\boldsymbol{w}$ and b are the parameters to be determined, and $\phi(\cdot)$ is a generic function. A deviation ε is used to evaluate the loss between the output $f(\mathbf{x})$ of the model and the true grain surface temperature y. In other words, when $|f(\mathbf{x}) - y| < \varepsilon$, the prediction result can be considered to be accurate.

The SVR problem can be formulated as follows.

$$\min_{\boldsymbol{w}, b} \quad \frac{1}{2}\|\boldsymbol{w}\|^2 + C \cdot \sum_{i=1}^{n} l_\varepsilon \left(f\left(\mathbf{x}_i\right) - y_i\right), \tag{7}$$

where C is a regularization constant and $l_\varepsilon(\cdot)$ is an insensitive loss function of ε. Adding a slack variable to the loss metric, problem in (7) can be transformed into a minimization problem (8) as follows.

$$\min_{\boldsymbol{w}, b, \xi_i, \hat{\xi}_i} \quad \frac{1}{2}\|\boldsymbol{w}\|^2 + C \cdot \sum_{i=1}^{n} \left(\xi_i + \hat{\xi}_i\right) \tag{8}$$

$$s.t. \quad f\left(\mathbf{x}_i\right) - y_i \leq \xi_i + \varepsilon,\ i = 1, 2, ..., n \tag{9}$$

$$y_i - f\left(\mathbf{x}_i\right) \leq \hat{\xi}_i + \varepsilon,\ i = 1, 2, ..., n \tag{10}$$

$$\xi_i \geq 0, \hat{\xi}_i \geq 0,\ i = 1, 2, ..., n, \tag{11}$$

where ξ_i and $\hat{\xi}_i$ are slack variables. To solve problem (8), we first obtain the following Lagrange function using the Lagrange multiplier method, defined as follows.

$$\begin{aligned} & L(\boldsymbol{w}, b, \alpha, \hat{\alpha}, \xi, \hat{\xi}, \mu, \hat{\mu}) \\ = \ & \frac{1}{2}\|\boldsymbol{w}\|^2 + C \cdot \sum_{i=1}^{n} \left(\xi_i + \hat{\xi}_i\right) - \sum_{i=1}^{n} \mu_i \cdot \xi_i - \\ & \sum_{i=1}^{n} \hat{\mu}_i \cdot \hat{\xi}_i + \sum_{i=1}^{n} \alpha_i \cdot \left(f\left(\mathbf{x}_i\right) - y_i - \varepsilon - \hat{\xi}_i\right) + \\ & \sum_{i=1}^{n} \hat{\alpha}_i \cdot \left(y_i - f\left(\mathbf{x}_i\right) - \varepsilon - \xi_i\right), \end{aligned} \tag{12}$$

where μ, $\hat{\mu}$, α, and $\hat{\alpha}$ are Lagrange multipliers. Applying the duality theory, the average temperature and humidity of the grain surface can be estimated as

$$f(\mathbf{x}) = \sum_{i=1}^{n} (\alpha_i - \hat{\alpha_i}) \cdot \phi(\mathbf{x}_i)^T \cdot \phi(\mathbf{x}) + b. \tag{13}$$

V. Performance Evaluation

In this section, we evaluate the performance of our proposed approach using real measurement data: the temperature data of grain storage at the *No. 1 Warehouse* in the Xishan District of Kunming, Yunnan, China for a period of 423 days. The meteorological data of the corresponding region and period are obtained from the China Meteorological Data Network (http://data.cma.cn/). We leverage SVR to predict the surface temperature of grain piles based on meteorological metric data.

Because of the poor thermal conductivity of the grain kernel itself and the thermal insulation of the silo wall of the granary, some samples cannot be linearly divided in the two dimensional space. Thus, we consider a *kernel function* to map the samples to a higher dimensional space, which can achieve a better separability performance. Under the Python 2.7 environment, the training process of the regression model is as follows. After outlier detection and data normalization, all calibrated meteorological factors are taken as independent variables, and the calibrated average temperature of grain stack surface as dependent variables, both of which are considered as input and output of SVR. In order to ensure that the same training set and test set are segmented in each run for the SVR model, the same random number seed is set [17]. In this paper, the linear kernel function, the polynomial kernel function, and the Gaussian RBF kernel function are used to predict the average temperature of the first layer of the stored grain pile [17], [18]. We discuss the detailed experimental results in the following.

A. Results with Different Kernel Functions

The linear kernel function is defined as follows.

$$k(\mathbf{x}, \mathbf{x}_i) = \mathbf{x} \cdot \mathbf{x}_i. \tag{14}$$

We use a linear kernel for the SVR model, where the dimension of the feature space is the same as the input space. It requires fewer parameters and also achieves a faster computational speed. The collected meteorological data of 423 days and the corresponding average temperature of the first layer of grain pile are used as data samples. The temperature of the first layer of grain pile per day corresponds to eight metrics of meteorology at the same time. We randomly select 80% of the samples as the training set, and the remaining 20% of the samples as the test set. The results of predicting the average temperature of the first layer of grain pile using the linear kernel function are presented in Fig. 6.

The polynomial kernel function is defined as follows.

$$k(\mathbf{x}, \mathbf{x}_i) = ((\mathbf{x} \cdot \mathbf{x}_i) + 1)^d, \tag{15}$$

where d represents the order of the polynomial. In our experiment, we set $d = 2$, which achieves a good performance. Due

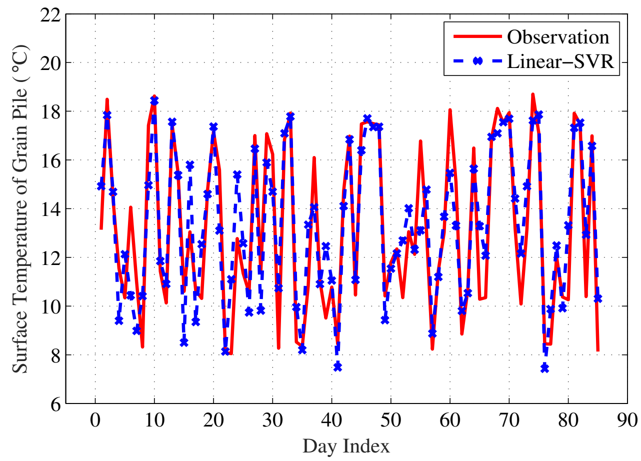


Fig. 6. Observation and predicted average temperature of the first layer of the stored grain pile using the linear kernel function.

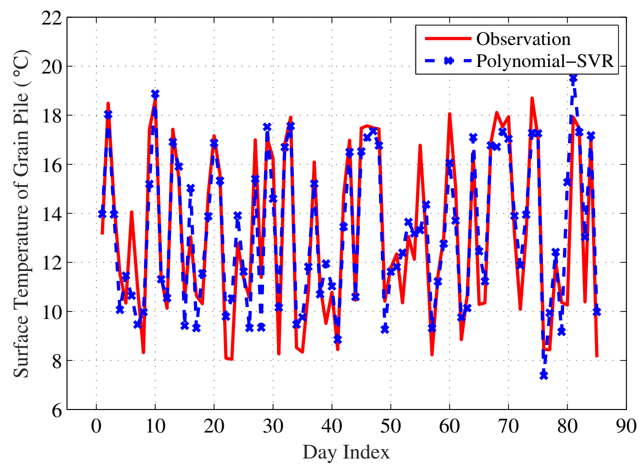


Fig. 7. Observed and predicted average temperature of the first layer of the stored grain pile using the polynomial kernel function.

to the ventilation and food turning operations during grain storage, the sample size collected within a time period is limited and the feature dimension is relatively small. The polynomial kernel function can map the low-dimensional input space to a high-dimensional feature space, but the corresponding computational complexity is higher. The results of predicting the average temperature of the first layer of grain pile obtained by the polynomial kernel function are shown in Fig. 7.

The Gaussian RBF kernel function is defined as follows.

$$k(\mathbf{x}, \mathbf{x}_i) = \exp\left(-\frac{\|\mathbf{x} - \mathbf{x}_i\|^2}{2\delta^2}\right), \tag{16}$$

where δ is the parameter of the Gaussian RBF. This is a locally strong kernel function that maps samples into a higher dimensional space. It can achieve a good performance for both large and small samples, and requires fewer parameters than the polynomial kernel function. The results of predicting the average temperature of the first layer of grain pile using the Gaussian RBF kernel function are shown in Fig. 8.

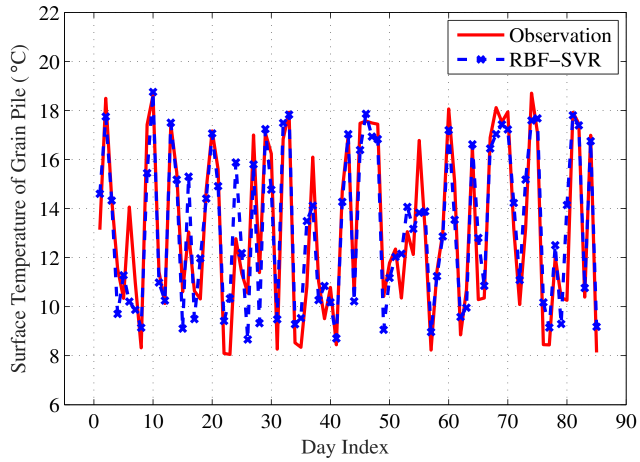


Fig. 8. Observed and predicted average temperature of the first layer of the stored grain pile using RBF.

B. Comparison

In order to quantitatively measure the prediction performance of the SVR method using different kernel functions, the root mean square error (RMSE) is used as the evaluation criteria. We obtain the RMSE results using the different kernel functions in the SVR model to predict the average temperature of the first layer of grain pile. We find that all the three schemes are quite accurate, while SVR with the Gaussian RBF kernel function achieves the smallest RMSE result. The polynomial kernel function achieves a 10.50% reduction over the linear kernel function. The Gaussian RBF kernel function achieves a reduction of 15.08% and 5.12% over the linear and polynomial kernel function, respectively.

VI. Conclusions

In this paper, we leveraged an SVR approach to predict the average temperature of the first layer of the stored grain pile using meteorological metrics. Due to the poor thermal conductivity of the grain kernel itself and the thermal insulation properties of the granary wall, the average temperature of the first layer of grain pile is usually delayed by a certain amount of time than the outside air temperature. Among eight factors of meteorology, there are three factors, including air temperature, 0cm ground temperature, and relative humidity, that have a greater impact on the average temperature of the first layer of grain pile. We applied SVR with three different types of kernel functions, i.e., the linear kernel function, the polynomial kernel function, and the Gaussian RBF kernel function, to perform regression analysis of the grain pile temperature. Grain temperature data measured from a real granary and the corresponding weather data were used in our study. We found all the three schemes achieved very accurate prediction of grain temperature, while SVR using the Gaussian RBF kernal function achieved the best prediction performance.

Acknowledgment

This work is supported in part by the Central Plains Scholar Project (172101510005), the National Key Research and Development Program of China (2017YFD0401003), the Natural Science Foundation of the Henan Province (152102210068), the Food Information Processing Key Laboratory of the Ministry of Education Open Fund (KFJJ-2017-108), and the NSF under Grant CNS-1702957, and by the Wireless Engineering Research and Education Center (WEREC) at Auburn University, Auburn, AL, USA.

References

[1] D. Vasisht, Z. Kapetanovic, J. Won, X. Jin, R. Chandra, S. Sinha, A. Kapoor, M. Sudarshan, and S. Stratman, "Farmbeats: An IoT platform for data-driven agriculture," in *USENIX NSDI 2017*, Boston, MA, Mar. 2017, pp. 515–529.

[2] S. M. Kamruzzaman, M. I. Pavel, M. A. Hoque, and S. R. Sabuj, "Promoting greenness with IoT-based plant growth system," in *Computational Intelligence and Sustainable Systems: EAI/Springer Innovations in Communication and Computing*, A. H., A. R., and O. C., Eds. Cham: Springer, 2019, pp. 235–253.

[3] L. Touseau and N. Le Sommer, "Contribution of the web of things and of the opportunistic computing to the smart agriculture: A practical experiment," *Future Internet*, vol. 11, no. 2, pp. 33:1–33:19, Feb. 2019.

[4] H. Jawad, R. Nordin, S. Gharghan, A. Jawad, and M. Ismail, "Energy-efficient wireless sensor networks for precision agriculture: A review," *MDPI Sensors*, vol. 17, no. 8, pp. 1–45, Aug. 2017.

[5] J. Bauer and N. Aschenbruck, "Design and implementation of an agricultural monitoring system for smart farming," in *Proc. 2018 IEEE IoT Vertical and Topical Summit on Agriculture*, Tuscany, Italy, May 2018, pp. 1–6.

[6] D. S. Jayas, "Storing grains for food security and sustainability," *Agricultural Research*, vol. 1, no. 1, pp. 21–24, Mar. 2012.

[7] C. B. Singh and J. M. Fielke, "Recent developments in stored grain sensors, monitoring and management technology," *IEEE Instrum. Meas. Mag.*, vol. 20, no. 3, pp. 32–55, June 2017.

[8] Z. Wu, H. Zhao, Y. Cao *et al.*, "Research progress on the applications of simulation technology in grain storage ecosystem," *J. Science & Technology of Cereals, Oils & Foods*, vol. 22, no. 1, pp. 1–6, Jan. 2014.

[9] F. Jian and D. S. Jayas, "The ecosystem approach to grain storage," *Springer Agricultural Research*, vol. 1, no. 2, pp. 148–156, June 2012.

[10] W. Yang, X. Wang, A. Song, and S. Mao, "Wi-Wheat: Contact-free wheat moisture detection using commodity WiFi," in *Proc. IEEE ICC 2018*, Kansas City, MO, May 2018, pp. 1–6.

[11] W. Yang, X. Wang, S. Cao, H. Wang, and S. Mao, "Multi-class wheat moisture detection with 5GHz Wi-Fi: A deep LSTM approach," in *Proc. ICCCN 2018*, Hangzhou, China, July/Aug. 2018, pp. 1–9.

[12] J. Yin, Z. Wu, Z. Zhang, X. Wu, and W. Wu, "Comparison and analysis of temperature field reappearance in stored grain of different warehouses," *Trans. Chinese Society of Agricultural Engineering*, vol. 31, no. 1, pp. 281–287, Jan. 2015.

[13] F. Wang, Z. Wang, L. Li, J. Huang, and Q. Wang, "Wireless granary temperature measurement node with function of low voltage detection," in *Proc. IEEE Inform. Technol., Netw., Electronic Automation Control Conf.*, Chongqing, China, May 2016, pp. 61–64.

[14] L. Yang, Z. Mao, Z. Jiang, and Z. Ren, "Remote detection system of granary temperature and moisture based on wireless transmission," *Trans. Chinese Society Agricultural Eng.*, vol. 2012, no. 4, Apr. 2012.

[15] Y. Wang, Y. Shen, S. Mao, X. Chen, and H. Zou, "LASSO & LSTM integrated temporal model for short-term solar intensity forecasting," *IEEE Internet of Things J.*, vol. 6, no. 2, pp. 2933–2944, Apr. 2019.

[16] N. Tang, S. Mao, Y. Wang, and R. Nelms, "Solar power generation forecasting with a LASSO-based approach," *IEEE Internet of Things Journal*, vol. 5, no. 2, pp. 1090–1099, Apr. 2018.

[17] A. J. Smola and B. Schölkopf, "A tutorial on support vector regression," *Springer Statistics & computing*, vol. 14, no. 3, pp. 199–222, Aug. 2004.

[18] C. Lopez-Martin, M. Azzeh, A. B. Nassif, and S. Banitaan, "v-SVR polynomial kernel for predicting the defect density in new software projects," arXiv preprint arXiv:1901.03362, Dec. 2018.