AMSE JOURNALS-AMSE IIETA publication-2017-Series: Advances B; Vol. 60; N°1; pp 43-56
Submitted Jan. 2017; Revised March 15, 2017, Accepted April 15, 2017

Fault Detection and Improvement Design of Temperature Sensor in Wood Carbonization Furnace

*Ming Yu, **Jian Wang, ***Meng Zhu, ****JiaShun Luo

* College of Information and Computer Engineering, Northeast Forestry University, Harbin, Heilongjiang, 150040, China, (yumingnefu@163.com)
** College of Information and Computer Engineering, Northeast Forestry University, Harbin, Heilongjiang, 150040, China, (Correspondingauthor: wang1342@foxmail.com)
*** College of Information and Computer Engineering, Northeast Forestry University, Harbin, Heilongjiang, 150040, China, (zhum913@163.com)
**** School of electrical and information engineering, Northeast Agricultural University, Harbin, Heilongjiang, 150040
China, (214552592@qq.com)

Abstract

As an important detection index in the carbonization process, wood carbonization furnace temperature ensures the reliability of wood carbonization control system. In this paper, a data-fusion-based method was proposed for fault detection and its improvements of carbonization furnace temperature sensor. By applying the data fusion algorithm to the control system of wood carbonization furnace, we obtained the modified data fusion method, with which we judged the working status of the temperature sensor in addition to the usage of the comprehensive supporting degree of sensors within the same group. A limited number of hardware backups were employed to guarantee the reliability of temperature measurement. The experiment result shows that our method performs effectively in enhancing the reliability and stability of wood charring furnace.

Key words

wood carbonization, temperature measurement, failure, confidence level

1. Introduction

Deeply-carbonized wood, also known as fully-carbonized wood or homogeneous carbonized wood, is born of ordinary wood processed at the high temperature of 200℃ or so. As its nutritional ingredients are destroyed, deeply-carbonized wood has good anti-corrosion and insect-resist properties. With restricted absorbent, functional group hemicellulose, the product has good physical properties. The real green products of deeply-carbonized wood prevent itself from corrosion and insects without relying on any harmful substances. In this way, not only has its service life been prolonged, but the carbonized wood will not exert any negative effect on human kinds, animals and the environment either during its lifespan or in the post-process of waste treatment [1]. The history of deeply-carbonized wood approaches a decade in Europe as the major displacement of the forbidden product of CCA anti-corrosion wood. Deeply-carbonized wood is widely used in aspects of wall panels, outdoor flooring, kitchen decoration, sauna room decoration, and furniture [2-4].

2. The Significance of Temperature Monitoring in Wood Carbonization Furnace

The wood carbonization technology is a kind of physical modification technology, by which the wood is placed in high temperature, anaerobic or low oxygen environment for a period of heat treatment. Such class of wood products is called carbonized Wood, of which the method differs from that of the conventional approaches of wood drying and charcoal-burning [5]. Carbonization temperature is usually controlled between 160℃ to 240℃. In the process of wood carbonization, steam is used to prevent the wood from burning, and the oxygen content in the treatment environment is controlled below 3% ~ 5%. The process of this technique is generally divided into three steps: (1) Temperature rising phase, including preheating, high-temperature drying and reheating stage; (2) Heat-treatment phase; (3) Cooling and balancing phase. During the process of wood carbonization, parameters of wood color, density, size, degree of carbonization and color uniformity of wood present significant temperature-varying properties. Hence, it is necessary to monitor the temperature changes in the furnace and the work of the heating tube, and regulate the in-furnace heat distribution, so as to ensure the reliability of the furnace temperature [6].

One of the premises of the reliable operation of wood carbonization control system is to ensure the reliability and accuracy of data collected at each of the in-furnace temperature points. However, electron devices may fail or work abnormally in such poor conditions of in-furnace environment as extra high initial moisture at the temperature-rising phase, high temperature in the heat-treatment phase, and the frequent in-furnace transportation of materials of wood panels, aluminum plates, etc. The question is raised about the way to identify sensor failure and to render the measured temperature closer to the actual one. Improper solutions to the problem will lead to the bad consequences of the rise in power consumption and the deviation from the reliable measurement results.

The carbonization furnace is not huge in dimension, while temperature is characterized by continuous variation, and thus there will never be abrupt temperature change. Instead, the temperature change is constrained by the limited furnace space, especially for monitoring points at relatively short distance from each other. Therefore, adjacent temperature monitoring points can serve as the points of reference. The temperature monitoring points are divided into several groups, each of which contains adjacent temperature sensors. Every temperature sensor measures its own temperature point parameters at the same time when providing reference for the measurement of the rest of temperature point members. The observed values of other sensors in the same group helps with comprehensive determination of the reliability of observed values of every sensor in the group----which indicates that whether sensors are in working order or not. If so, the temperature value of the spot will be determined with the observed value of sensor on original test points; if the sensor is regarded as in abnormal condition, the backup sensor will be started for measured temperature value of this test point.

In this paper, we propose a fast and effective way to diagnose faulty sensors in real time, and use software and hardware backup to improve the reliability of temperature. With this method, the redundant design for all temperature measurement points, thus ensuring the reliability of temperature measurement and improving the accuracy of the wood carbonization control system [7].

3. Calculation of The Confidence Degree Of Measured Temperature Based On Data Fusion

Multi-sensor information fusion is the process of information processing and data processing, which is based on the computer technology. According to some specific criteria, information and data from multi-sensor or multi-source are analyzed and synthesized automatically to complete the target of decision-making and estimation. For a certain feature of the environment, it is possible to obtain multiple copies of information from multiple sensors, which are redundant and reliable at different degrees [8]. By using the multi-sensor information fusion method, we are able to extract more accurate and reliable information from raw data. In addition, the redundancy of information can improve the system stability, so that the operation of the whole system will not be interrupted by the failure of a single sensor. Multi-sensor data fusion technology is widely used in various fields such as military, satellite, aerospace and industrial applications [9, 10].

As carbonization furnace temperature sensors are of the same model, the homogeneous sensor fusion method is adoptable in our research. We have more than one temperature points to be measured, and thus the temperature difference varies with the distance between points. Therefore, the spatial distance between sensors is one of our indexes of data fusion [11]. The longer the spatial distance between a pair of sensors is, the greater the allowed temperature difference is, and the smaller the weight of the comprehensive support degree is.

The spatial distance between a set of N sensors is measured as C_{ij} (i= 1, 2, …, N; j=1, 2, …, N). The shortest spatial distance is set as 0.4 and the longest as 1; we normalize the matrix C and converted the normalized matrix C into matrix Y. Therefore, Y_{ij} denotes the standard spatial distance between the ith sensor and the jth sensor [12-14].

$$Y=\begin{bmatrix} Y_{11} & Y_{12} & \ldots & Y_{1N} \\ Y_{21} & Y_{22} & \ldots & Y_{2N} \\ . & . & & . \\ Y_{N1} & Y_{N2} & \ldots & Y_{NN} \end{bmatrix} \tag{1}$$

We let the measured temperature of the N sensors be respective $x_1, x_2, \ldots, x_N$. The measured temperature of an arbitrary sensor is obtained randomly, obeying normal distribution. In this case, the measured temperature of the ith sensor can be expressed by Gaussian probability density function as follows:

$$p_i=\frac{1}{\sqrt{2\pi}}\exp\left[-\frac{1}{2\sigma_i^2}(x-x_i)^2\right], i=1,2,3,........N \tag{2}$$

The jth sensor related support degree d_{ij} of the ith sensor is expressed as:

$$d_{ij}=2\int_{x_i}^{x_j}p_i(x|x_i)dx=p(|Z|\leq|x_i-x_j|/\sigma_j) \tag{3}$$

According to equation (2), as $\sigma_i \neq \sigma_j$, we have $d_{ij} \neq d_{ji}$. Considering that all the sensors are homogeneous, i.e. their support degree is asymmetric, we also have $d_{ij}=d_{ji}$. Meanwhile, the spatial distance between sensors should be substituted into equation (3) as an influencing factor:

$$d_{ij}=d_{ji}=P(|Z|\leq\frac{|x_i-x_j|}{2Y_{ij}\sqrt{\sigma_i^2+\sigma_j^2}})=2\int_0^{\frac{|x_i-x_j|}{2Y_{ij}\sqrt{\sigma_i^2+\sigma_j^2}}}\frac{1}{\sqrt{2\pi}}e^{\frac{x^2}{2}}dx \tag{4}$$

The confidence matrix is obtained as

$$D=\begin{bmatrix} d_{11} & d_{12} & \ldots & d_{1n} \\ d_{21} & d_{22} & \ldots & d_{2n} \\ . & . & & . \\ d_{n1} & d_{n2} & \ldots & d_{nn} \end{bmatrix} \tag{5}$$

According to the confidence distance between sensors, we acquire their support matrix R= I-D, in which I is the unit matrix at the size of n×n. D and R are both asymmetric positive real matrixes. Therefore, the maximum eigenvalue of R $\lambda > 0$. We let the corresponding characteristic vector be $\eta=(\eta_1, \eta_2, \ldots, \eta_n,)$, and thus $R\eta=\lambda\eta$. The formula is expanded as:

$$\lambda\eta_k=r_{k1}\eta_1+r_{k2}\eta_2+\ldots+r_{kn}\eta_n, k=1,2,\ldots,n \tag{6}$$

Where $\lambda\eta_k$ is the sensor's comprehensive support degree of the kth sensor. To normalize the support degree, we define the normalized comprehensive support degreeαk:

$$\alpha_k = \frac{\lambda\eta_k}{\sum_{i=1}^{n}\lambda\eta_i} = \frac{\eta_k}{\sum_{j=1}^{n}\eta_j}, k = 1,2,...,n \tag{7}$$

According to expert experience and the results of multiple tests, we determine the thresholdβ and the temperature value at every temperature point as

$$\begin{cases} y_k = x_k, B_k > \beta \\ y_k = y_a(y_b), B_k \leq \beta \end{cases} \tag{8}$$

Where x_k represents the output of the kth sensor, y_k is the last measured value of the kth temperature point. As can be seen from equation (8), for the kth temperature point, the measured value has 2 types of expression: if the kth sensor at this point works normally, the temperature of the point will be decided by the measured value of the kth sensor; if the kth sensor works abnormally, the corresponding backup equipment will be launched. The same method will be used to judge the confidence degree of the backup equipment. The backup equipment will replace the failed equipment if the confidence degree is high enough.

4. Historical Data Validation Cases

In this paper, all the temperature sensors in the furnace are divided according to groups. Wood charring furnace is usually composed of 3-5 groups of sensors. Each of the groups contains 5 to 6 neighboring sensors and 2 sets of temperature measurement hardware backup. Figure 1 is the distribution map of a measurement sensor and a backup sensor within the same group, where ● represents the measurement sensor, ○ for the backup sensor. Sensor No.6 provides backups of sensors No.1-3, while sensor No.7 provides backups of sensors No.4-5. If sensors 1-5 are working, the backup sensor data will be ignored by the system. The measured value of each sensor depends on the support and its degree of the measured values of the rest of sensor members in the same group. If its support degree is low, the sensor may fail. In this case, the corresponding backup equipment will be launched. The same method will be used to judge the confidence degree of the backup equipment. The backup equipment will replace the failed equipment if the confidence degree is high enough.

The process of temperature measurement is: (1) according to the expectations, variances and spatial distances of each sensor, we calculate the confidence distance matrix D and the support matrix R. (2) We calculate the maximum eigenvalue of the R matrix and the corresponding eigenvector; (3) We calculate the comprehensive support of each sensor; (4) We calculate the maximum support vector of the sensor matrix;) We determine the output of the test points based on the relationship between the overall support and the threshold. Table 1 is the measured data obtained from all the normally working sensors in the group[15].

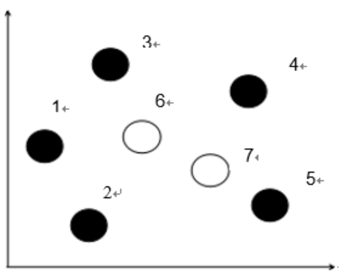

Fig.1. Sensor Layout

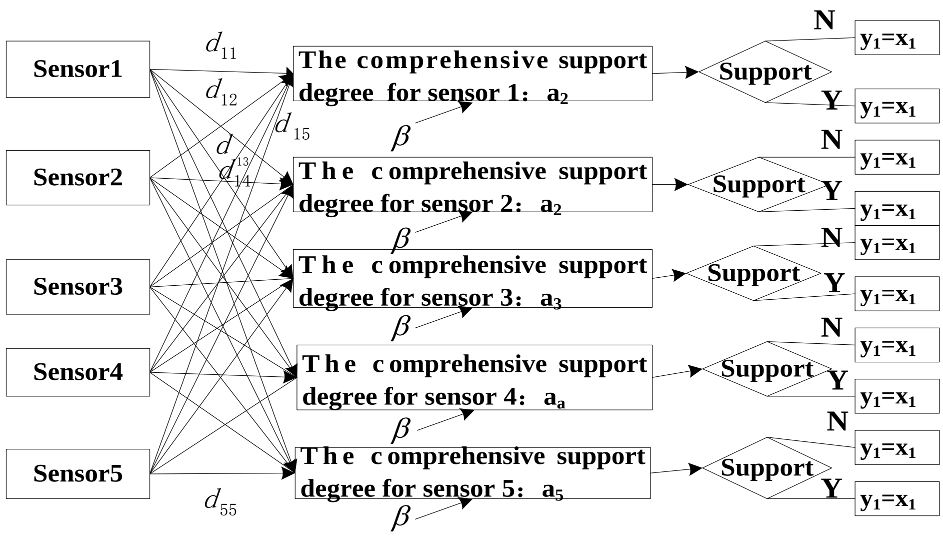

Fig.2. The Flow Chart of Sensor Temperature Measurement

Table 1 lists the historical data of a group of sensors when the carbonization furnace is in the heat-treatment phase.

Tab.1. The Historical Data at Normal Work

Sensor	1	2	3	4	5
Expectation	202.18	203.45	204.05	204.26	202.03
variance	0.23	0.31	0.23	0.41	0.44

According to the position of the sensor, we obtain the spatial distance matrix L as

$$L=\begin{bmatrix} 0 & 0.54 & 0.65 & 0.93 & 1 \\ 0.54 & 0 & 0.75 & 0.87 & 0.77 \\ 0.65 & 0.75 & 0 & 0.56 & 0.82 \\ 0.93 & 0.87 & 0.56 & 0 & 0.50 \\ 1 & 0.77 & 0.82 & 0.50 & 0 \end{bmatrix} \tag{9}$$

With the parameters of spatial distance matrix L, and the expectations and variances of the measured temperature of each sensor in the group, we obtain the confidence distance matrix as

$$D=\begin{bmatrix} 0 & 0.16 & 0.07 & 0.06 & 0.42 \\ 0.16 & 0 & 0.84 & 0.85 & 0.13 \\ 0.07 & 0.84 & 0 & 0.87 & 0.14 \\ 0.06 & 0.85 & 0.87 & 0 & 0.24 \\ 0.42 & 0.13 & 0.14 & 0.24 & 0 \end{bmatrix} \tag{10}$$

We calculate the eigenvalue of the matrix as 2.7884, and the corresponding eigenvector as [-0.30, -0.54, -0.63, -0.65, -0.50]^T, where the values of $\alpha_1 \sim \alpha_5$ are 0.07, 0.21, 0.25, 0.27 and 0.12, respectively. The threshold is defined as 0. As can be seen from the said data, the comprehensive support degree of sensors No.2-4 is relatively large, which conforms to the actual situations of matrix L, the measured data (see Table 1), and the spatial layout (see Figure 1). The fusion-based calculation results show that none of the 5 sensors in this group work abnormally or fail. The temperature measured points of sensors No.1-5 are determined according to sensor outputs (202.18, 203.45, 204.56, 204.26, 202.03, respectively).

Tab.2. The Historical Data Measured by the 5 Sensors When the Sensor No.3 Cannot Work Normally

Sensor	1	2	3	4	5
Expectation	202.45	202.38	240.56	203.34	203.38
variance	0.26	0.33	2.28	0.43	0.31

According to equation (3), the confidence distance matrix D is

$$D = \begin{bmatrix} 0 & 0.81 & 1 & 0.75 & 0.73 \\ 0.81 & 0 & 1 & 0.61 & 0.58 \\ 1 & 1 & 0 & 1 & 1 \\ 0.75 & 0.61 & 1 & 0 & 0.87 \\ 0.73 & 0.58 & 1 & 0.87 & 0 \end{bmatrix} \tag{11}$$

We calculate the eigenvalue of the matrix as 4.3662, and the corresponding eigenvector as is $[0.57,0.61,0,0.28,0.32]^T$, where the values of $\alpha_1 \sim \alpha_5$ are 0 0.29, 0.31, 0, 0.14,and 0.15, respectively. The threshold is defined as 0. The result of the fusion calculation shows that the sensor No.3 fails, which invalidates its measured value. The corresponding backup sensor No. 6 sensor is started, whose measured value and variance are 203.51 and 0.23, respectively. The comprehensive support degree is also obtained through the data fusion. The result shows that the measured value of sensor b is valid, and thus sensor No.3 is replaced by sensor b. Therefore, the five temperature measured points' outputs are 202.45, 202.38, 203.51, 203.34, and 203.28, respectively.

Figure 3 is a set of broken lines of the temperature measured at the heat-treatment stage within 12 minutes, without the use of data fusion technology. As can be seen from Figure 3, there appear some catastrophe points in the unsmooth red line. What is more, the temperature errors have been inputted in the carbonization control system, which renders the technical process control less accurate. The blue line shows the temperature monitored by the backup sensor, which basically complies with the actual carbonization process [16].

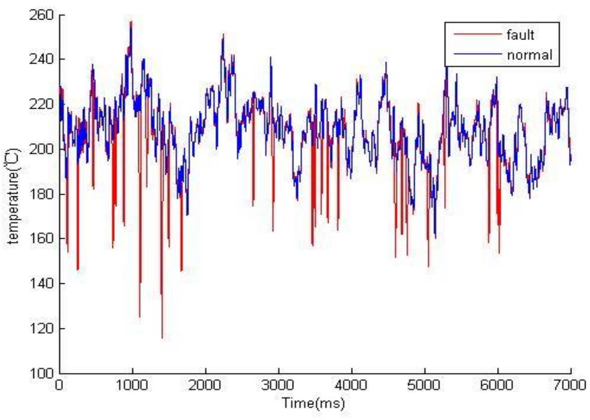

Fig.3. The Comparison Diagram of Temperature Monitoring

5. Case Verification

The experiment object is 650mm × 80mm × 20mm fraxinus mandshurica. The targeted carbonization depth and color are 6mm and dark brown, respectively. Figure 4 shows the layout of a single slice of wood specimen and the sensors. The proposed method in the paper is used to optimize temperature data processing, while the traditional PID method is used for output control. The carbonization test spends the total of 220 minutes, constituting three stages. The test begins at 10:20, at the initial temperature of 27.4℃. Electric heaters and steam heaters provide heat simultaneously (there are four groups of electric heaters whose gross power is 60kw; all of them are angle joint). Wind from the draught fan blows towards the gate. After the temperature rises to 104.4 ℃, the steam heaters stop working; after the temperature reaches 201.6 ℃ in 11:33 am, the electric heaters stop working. At 80 ℃, the moisture content of wood should be increases manually. The whole test lasts 73 mins. In the early stage of the temperature-rising process, the temperature rockets according to requirements; in the latter stage, the temperature rises smoothly. The heat change rate is a direct contributing factor to the carbonization effect in the latter stage of wood carbonization. Figure 5 shows the furnace temperature change at the continuous temperature-rising process, where the x coordinate is the carbonization time, and the y coordinate is the monitored furnace temperature.

Fig.4. The Sensor Layout of Wood Carbonization Test

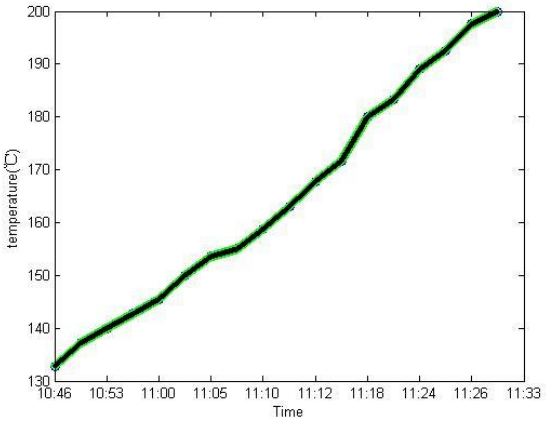

Fig.5. The Curve of Temperature Change in the Temperature-Rising Process

At 11:33, the temperature reaches 201.6℃. The heat-treatment timespan is 10mins, during which the temperature is required to remain at around 200℃. Great temperature change is forbidden, or otherwise the depth or color of carbonized wood will deviate from the targeted one. Figure 6 is the furnace temperature change in the continuous heat-treatment process.

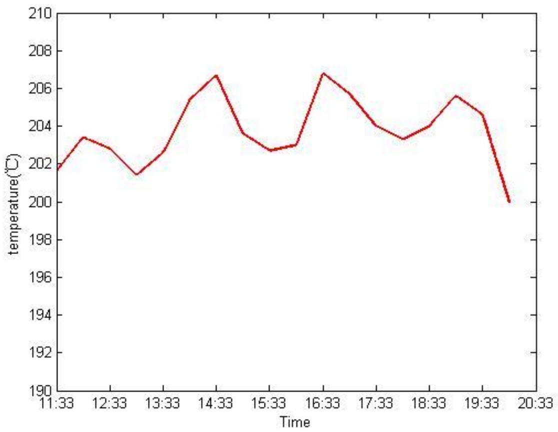

Fig.6. The Furnace Temperature Change in the Continuous Heat-Treatment Process

At 11:43 am, all the electric heaters are turned off, and the vent hole is opened for thermal discharge in the cooling stage, during which the drought fan continues working. In this stage, the temperature should be reduced slowly and controllably. Figure 7 is the curve of temperature change in the temperature-decreasing process.

The carbonized wood has uniform color and depth, as a result of the satisfactory carbonization technique control. Figure 8 is the appearance of carbonization wood.

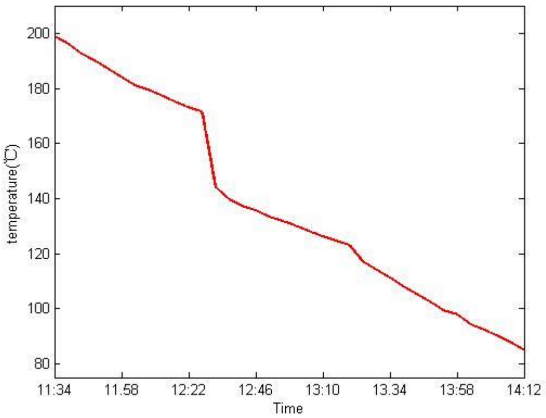

Fig.7. The Curve of Temperature Change in the Temperature-Decreasing Process

Fig.8. The Appearance of Carbonization Wood

6. Conclusion

The experimental results show that our design method combines software backup and hardware backup, and handles the redundancy design of temperature measurement with a limited number of hardware apparatuses. In this way, the temperature measurement and control system is rendered more reliable. Moreover, it lessens the seriousness of the problems of power loss, cumbersomeness and oversize which are raised in redundancy design.

Acknowledgements

This work was supported by the Fundamental Research Funds for the Central Universities (2572015BB22) and National Science and Technology Project (2014BAF11B01) and Fundamental Research Funds for the Central Universities (DL11AB01).

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