Sensors and Materials, Vol. 34, No. 8 (2022) 3285–3298
MYU Tokyo

S & M 3041

Wireless Sensor Layout Optimization of Raw Tobacco Pallets Based on Swarm Intelligence

Yueming Xu,[1] Shiyun Chen,[2] Bin Chen,[1] Jilai Zhou,[1] Renjie Xu,[1] and Nan Pan[2*]

[1]Logistics Center, Hongyun Honghe Group Co., Ltd., Kunming 650202, China
[2]Faculty of Civil Aviation and Aeronautics, Kunming University of Science & Technology, Kunming 650500, China

(Received February 25, 2022; accepted July 15, 2022)

Keywords: wireless sensors, layout optimization, particle swarm optimization, LSTM neural network

Temperature data inside pallets are used as important data indicators for raw tobacco storage and maintenance. To improve the monitoring effect of wireless sensors in raw tobacco pallets, the layout optimization model of wireless sensors in a three-dimensional complex environment is constructed, a multi-objective function with the smallest sensor layout cost and the largest monitoring range is established, and an improved particle swarm optimization (IPSO) is designed to obtain preliminary results. The layout of wireless sensors is optimized and then the long short-term memory (LSTM) neural network algorithm is used to predict the temperature data in a cigarette pallet to achieve the secondary optimization of the sensor layout. Finally, on the basis of actual temperature data in raw tobacco pallets, a simulation environment model is established and verified by simulation experiments. Simulation results show that the sensor layout optimization method proposed in this paper can effectively reduce the number of sensors arranged and, at the same time, allow enterprises to effectively minimize the cost of raw tobacco storage and maintenance.

1. Introduction

Under the current structure of China's tobacco industry, raw tobacco storage areas of tobacco groups are set up according to administrative regions, with each tobacco group company having a corresponding raw tobacco storage yard, and each raw tobacco yard generally has multiple raw tobacco pallets, each of which is an independent environment. According to the management regulations of the raw tobacco yard, all packs entering the yard need to be sorted and stacked according to the year, variety, origin, grade, moisture content, and other relevant information of tobacco leaves. However, as there are usually omissions and lapses during packet inspection, the environment inside the pallets becomes complex and uncertain. Therefore, the core problem in the maintenance of raw tobacco pallets is still the monitoring of mold information in complex and uncertain environments.

Sensor layout planning is an essential aspect of tobacco information monitoring in a raw tobacco yard, as raw tobacco requires a strict monitoring of temperature and humidity changes inside the pallets during maintenance to inhibit the growth of molds and mildews inside the pallets,(1) which

*Corresponding author: e-mail: nanpan@kust.edu.cn
https://doi.org/10.18494/SAM3879

ISSN 0914-4935 © MYU K.K.
https://myukk.org/

can cause the tobacco to fail to achieve the best mellowing during maintenance. Therefore, the deployment of raw tobacco maintenance sensors is a multi-objective wireless sensor network (WSN) deployment problem involving many constraints,[2] which is also one of the core problems of raw tobacco maintenance information monitoring.

There have been several studies on the deployment of WSNs at home and abroad. For example, to improve network lifetime and network feasibility, a new method of data transmission based on WSN with low latency and energy balance was proposed by Pandey and Hegde on the basis of small-world characteristics.[3] Elhoseny *et al.*[4] proposed a genetic-algorithm-based K-coverage model to extend the operational lifetime of WSNs after the wireless sensors run out of energy and cannot effectively monitor the monitoring targets. Feng *et al.*[5] designed an adaptive particle swarm optimization (PSO) to solve such problems in order to ensure that the monitoring range formed by the WSN deployment can effectively meet the requirements of the monitoring environment. Liu *et al.*[6] proposed a distributed cuckoo algorithm for optimizing the layout of wireless sensor nodes to address the problems of low node utilization and low coverage of wireless sensor networks. In addition, intelligent algorithms such as simulated annealing,[7] ant colony optimization,[8] and PSO[9] are also widely used in solving layout optimization problems.

In terms of sensor information monitoring, there are a few studies related to the optimization of the sensor layout. Xu *et al.*[10] formed an information matrix based on the modal matrix and arranged it according to the preset points, and further eliminated the points with smaller contributions by analyzing the contribution of the modal matrix of each point, and finally optimized the information matrix. Hao *et al.*[11] used the K-means clustering algorithm to find the temperature anomalies in the spatial range of the grain bin, then used multiple-response analysis to screen the feature points to form a preliminary layout scheme, and finally used the ARIMA algorithm to test the feature points for prediction and to correct the layout scheme to optimize the sensor layout. Li *et al.*[12] used ANSYS FLUENT analysis software to simulate the temperature field distribution in a mushroom room, which in turn guided the arrangement of the sensor monitoring system in the mushroom room in order to optimize the layout of temperature sensors. By the computational fluid dynamics (CFD) simulation method, Jia *et al.*[13] and Zhao *et al.*[14] determined the optimal arrangement of temperature sensors by simulating and analyzing the temperature field of a plant factory. Jin[15] restored the temperature field of an unknown point by interpolating the data of a limited number of temperature nodes at a certain moment on the basis of the spatial interpolation theory and further optimized the layout of the temperature sensor through a genetic algorithm.

From these studies, it can be seen that simulation, data interpolation, and optimization algorithms have been widely used in the field of sensor layout and have achieved certain results, but the following problems still exist in the current research on sensor layout planning.

(1) At this stage, most of the research is mainly focused on WSN models and algorithms, whereas research on sensor layout optimization, such as in tobacco mildew information monitoring, is nearly missing.

(2) In the study of sensor layout optimization, the existing research is very simplified when considering sensor constraints.

(3) Most of the current research does not incorporate a practical application context, which causes considerable difficulties in the practical application of models and algorithms.

In this study, we address the problems of incomplete monitoring of mildew information and high equipment investment costs in current tobacco leaf maintenance, and establish a wireless sensor layout optimization model in the context of tobacco leaf maintenance in tobacco logistics centers. The multi-objective sensor layout optimization model with minimum sensor placement cost and mildew information monitoring coverage is constructed on the basis of temperature data for a certain time period and solved using an improved particle swarm optimization (IPSO) based on an adaptive strategy to determine the location of the sensors, thus achieving layout optimization with minimum sensor placement cost and maximum coverage. Experimental results show that the proposed solution can be effectively used in raw tobacco maintenance monitoring.

2. Mathematical Model for Sensor Layout Optimization

2.1 Problem description

The traditional deployment methods of wireless sensors are uniform deployment and manual experience deployment, but these two deployment methods usually have too many deployments of wireless sensors, a low monitoring coverage rate or too many monitoring overlaps of wireless sensors. These problems lead to a large amount of waste of wireless sensor resources. In this study, we rely on the temperature and humidity monitoring data of some raw tobacco pallets in a raw tobacco yard area of Hongyun Honghe Tobacco (Group) Co., Ltd. to build a wireless sensor layout optimization model to maximize the utilization of wireless sensor monitoring resources.

2.2 Model assumptions

(1) The temperature sensors used all have the same sensing radius.
(2) The grid method is used to classify raw tobacco pallets.
(3) The weather conditions outside the chimney will not change suddenly and will not affect the inside of the chimney.
(4) The signal transmission of the wireless sensor is not interfered in the pallets, and the entire pallet area is covered by the wireless sensor.

2.3 Model construction

Let the sensing radius of the adopted temperature sensor be R. In this paper, the sensing radius of the sensor is defined as the product of the thermal diffusivity of the temperature[16,17] and the duration of the sensor monitoring interval.

$$R = \alpha \cdot \overline{t} \tag{1}$$

$$\alpha = \frac{\lambda}{C_V} \tag{2}$$

Here, R is the sensing radius of the wireless sensor, $\overline{t}$ is the time interval between the two monitoring sessions, α is the thermal diffusivity of the tobacco leaf, λ is the thermal conductivity of the tobacco leaf, and C_V is the volumetric heat capacity $C_V=\rho^*C_P$.

Let $T=\{T_1^R,T_2^R,\cdots,T_m^R\}$ be the set of spatial raster points inside a raw tobacco pallet, (x_i^R,y_i^R,z_i^R) is the position of any raster point T_i^R in the raw tobacco pallet space, $P=\{P_1^W,P_2^W,\cdots,P_2^W\}$ is a collection of wireless sensors within a raw tobacco pallet, and (x_j^W,y_j^W,z_j^W) is the position of any sensor P_j^W in the raw tobacco pallet space. Then, the location of any sensor A and the location of any pallet grid point B are expressed using the Euclidean distance as

$$d(P_j^W,T_i^R)=\sqrt{(x_j^W-x_i^R)^2+(y_j^W-y_i^R)^2+(z_j^W-z_i^W)^2}\,. \tag{3}$$

In this paper, the relationship between the storage temperature and the specific growth rate of molds is used to define the coverage weight of each grid point inside the original tobacco stack, i.e.,

$$\ln(u)=C_0+\frac{C_1}{T+273}+\frac{C_2}{(T+273)^2}, \tag{4}$$

$$w_i^R=\ln(u_i). \tag{5}$$

Here, C_0, C_1, and C_2 are coefficients, T is the storage temperature (°C), and ln(ui) is the specific growth rate of the ith raster point affected by the temperature at that point.

Let the monitoring coverage weight of any grid point T_i^R inside the raw tobacco pallet be w_i^R. Then, the monitoring coverage rate of any wireless sensor j to a certain area inside the raw cigarette pallet can be defined by the weight of each location point in the area and can be expressed as

$$w_j^W=\sum_{i=1}^{m}w_i^R\cdot X_i^j,\ j\in\{1,2,\cdots,n\}\,, \tag{6}$$

$$X_i^j=\begin{cases}1, d(P_j^W,T_i^R)\le R,\\ 0, d(P_j^W,T_i^R)>R.\end{cases} \tag{7}$$

Here, w_j^W is the coverage weight of the grid points of sensor j in the raw tobacco pallet and X_i^j is a 0-1 variable. When the distance from any grid position in the raw tobacco pallet to sensor j is less than the sensor's sensing radius, $X_i^j=1$; otherwise, $X_i^j=0$.

The total coverage rate of a certain cigarette pallet wireless sensor to the raw tobacco pallet can be expressed as

$$w_{all}^W=\sum_{j=1}^{n}w_j^W\,. \tag{8}$$

According to the management requirements of the raw tobacco pallets of Hongyun Honghe Tobacco (Group) Co., Ltd., a small number of wireless sensors are needed to monitor as much mildew information of the pallets as possible. Therefore, the available optimization goal is

$$\max : f = \frac{w_{all}^{W}}{n}. \tag{9}$$

Constraints:

The number of wireless sensors should not exceed the upper limit of the maximum arrangement of each raw tobacco pallet:

$$n < n_{\max}^{W}, n \in Z. \tag{10}$$

$n_{\max}^{W}$ is the upper limit of the maximum number of raw tobacco pallets given by the enterprise.

The layout of the wireless sensor should be inside the raw tobacco pallet and not beyond the raw tobacco pallet space:

$$\begin{cases} x_{\min}^{R} < x_j^{W} < x_{\max}^{R} \\ y_{\min}^{R} < y_j^{W} < y_{\max}^{R} \\ z_{\min}^{R} < z_j^{W} < z_{\max}^{R} \end{cases}, j \in \{1, 2, \cdots, n\}. \tag{11}$$

Here, $x_{\min}^{R}$, $y_{\min}^{R}$, $z_{\min}^{R}$, $x_{\max}^{R}$, $y_{\max}^{R}$, and $z_{\max}^{R}$ are the margins of the wireless sensor in the pallet space,

$$\sqrt{2}R \le d(P_i^{W}, P_j^{W}),\ \forall P_i^{W} \in P. \tag{12}$$

Here, $d(P_i^{W}, P_j^{W})$ is the distance between any wireless sensors.

3. Algorithm Description

3.1 Traditional PSO

PSO is a swarm intelligence algorithm proposed in 1995. It solves the optimization problem by imitating the foraging and predation behaviors of birds. The optimization of PSO originates from the information interaction between particles and the update of particle speed and position. In this algorithm, the position of each particle represents a solution of the problem, and the position of the particle in the next iteration is determined by the position and velocity of the particle. The population structure of PSO is

$$U^g \to \left\{ \begin{array}{l} X_1^g \to \left\{ \begin{array}{l} v_1^1, v_1^2, \cdots\cdots, v_1^D \\ x_1^1, x_1^2, \cdots\cdots, x_1^D \end{array} \right\} \\ X_2^g \to \left\{ \begin{array}{l} v_2^1, v_2^2, \cdots\cdots, v_2^D \\ x_2^1, x_2^2, \cdots\cdots, x_2^D \end{array} \right\} \\ \qquad \vdots \\ X_{NP}^g \to \left\{ \begin{array}{l} v_{NP}^1, v_{NP}^2, \cdots\cdots, v_{NP}^D \\ x_{NP}^1, x_{NP}^2, \cdots\cdots, x_{NP}^D \end{array} \right\} \end{array} \right\}. \tag{13}$$

Here, U^g represents the population in the gth iteration, X_i^g represents the individual in the gth iteration, v_i^j represents the speed of the ith individual in the jth dimension, x_i^j represents the position of the ith individual on the jth dimension, NP is the population size, and D is the problem dimension.

In the traditional PSO, the initial position of the particles is generated by random numbers. In each iteration, the particle will update its position by tracking two positions: one is the optimal solution found in the iteration process and the other is the optimal solution found by all particles in the iteration process, such as

$$v_i^j = w \times v_i^j + c1 \times r1 \times (x_{ipbest}^j - x_i^j) + c2 \times r2 \times (x_{gbest}^j - x_i^j), \tag{14}$$

$$x_i^j = x_i^j + v_i^j . \tag{15}$$

Here, w is the weight of inertia, $c1$ and $c2$ are the learning factors, $r1$ and $r2$ are random numbers between 0 and 1, and X_{ipbest} and X_{gbest} respectively represent the historical optimal solution of the ith individual and the global optimal solution of the population.

The basic steps of the traditional PSO are as follows.

Step 1. Initialize the parameters and generate the initial population in a random manner.

Step 2. Calculate the fitness function value of the individuals in the population, update the individual and global extreme values, and save the corresponding extreme points.

Step 3. Update the speed of each individual and re-assign the speed that violates the boundary conditions.

Step 4. Update the position of each individual and re-assign the position that violates the boundary conditions.

Step 5. Exit the loop when the maximum number of iterations is reached; otherwise, return to Step 2.

The traditional PSO is widely used in various optimization problems because of its low complexity, easy implementation, and good convergence. However, as the model complexity of the optimization model gradually increases, PSO is used in large-scale optimization problems. It is easy to fall into the local optimum, so in this paper, we propose an IPSO to achieve better results when solving large-scale problems.

3.2 Improved particle swarm algorithm

3.2.1 Differential crossover strategy

In the traditional PSO algorithm, the individual location update uses the search method shown in Refs. 14 and 15. This update method may cause the individual to fall into the local extreme point during the movement, causing the algorithm to fall into the local optimum or even become stagnant. To solve this problem, the mechanism of the differential evolution algorithm is used as reference, the differential crossover strategy is introduced, and the mutant population is generated through

$$\begin{cases} V_i^g \to \{vx_i^1, vx_i^2, \cdots\cdots, vx_i^D\}, \\ V_i^g = X_i^g + F \times (X_{r3}^g - X_{r4}^g), \end{cases} \tag{16}$$

where F represents the difference coefficient, $r3$ and $r4$ are random integers between 1 and NP, and after the mutant population is obtained, the cross operation is performed with the original population to obtain the cross population, as shown in Eq. (17).

$$\begin{cases} C_i^g \to \{c_i^1, c_i^2, \cdots\cdots, c_i^D\} \\ c_i^j = \begin{cases} vx_i^j & r5 < CR \text{ or } j = rnd \\ x_i^j & otherwise \end{cases} \end{cases} \tag{17}$$

3.2.2 Foraging selection strategy

In the traditional PSO, the particles will choose to directly accept the new position after the position is updated, although the fitness value of the new position is worse than that of the original position. This may lead to the loss of high-quality solutions, which will decrease the convergence speed of the algorithm. To solve this problem, a foraging selection strategy is introduced. Before the location update, the structure and information of the original population are completely copied to obtain a new population. The new population will replace the original population for differential and crossover operation. The original population still implements the update strategy of the traditional particle swarm algorithm. After the location update is completed, the new population will merge with the original population to form a selection population with population size 2NP. By sorting the fitness values, better NP individuals are selected through the greedy strategy, and the next iteration is entered.

In summary, the basic steps of the improved particle swarm algorithm are as follows.

Step 1. Initialize the parameters and generate the initial population in a random manner.

Step 2. Calculate the fitness function value of the individuals in the population, update the individual and global extreme values, and save the corresponding extreme points.

Step 3. Copy the structure and information of the population to obtain a new population, and the new population replaces the original population for differential crossover operation.

Step 4. Update the speed of each individual in the original population and re-assign the speed that violates the boundary conditions.

Step 5. Update the position of each individual in the original population and re-assign the position that violates the boundary conditions.

Step 6. Perform a differential crossover strategy for each individual in the new population to generate a cross population.

Step 7. Combine the updated cross population with the original population, sort the fitness values, and select the better individual to enter the next iteration.

Step 8. When the maximum number of iterations is reached, exit the loop; otherwise, return to Step 2.

4. Experimental Testing

To verify the effectiveness of the algorithm designed in this paper, simulation experiments with the traditional PSO are compared with the IPSO proposed in this paper to effectively illustrate the effectiveness of the proposed algorithm.

4.1 Experimental environment

In this paper, we present a simulation based on a week's worth of temperature monitoring data from the logistics center of Hongyun Honghe Tobacco (Group) Co., Ltd., and a four-dimensional data interpolation method was used to fit the monitoring data and visualize the output to build an optimized sensor layout model. The simulation experiment environment used in this paper is Intel i7-9750H CPU (2.60 GHz), 16 Gb of RAM, and MATLAB R2016b simulation software. Through the investigation of the cargo yard under the logistics center of Hongyun Honghe Tobacco (Group) Co., Ltd., it can be known that the maximum deployment limit of sensors is $n_{\max}^{W} = 80$, the density of the raw tobacco leaf is ρ = 200 kg/m^3, and the heat–melt ratio of the tobacco leaf is C_P = 1.83 kJ/kg°C. The time interval between the two monitoring sessions of the sensor is $30\,\mathrm{min}$, the thermal conductivity of the raw tobacco leaf is λ = 0.09132, and the maximum boundaries of the pallet are $x_{\max}^{R} = 9.7$, $y_{\max}^{R} = 4$, and $z_{\max}^{R} = 3.2$. The temperature monitoring data interpolation and visualization analysis diagrams through Matlab tools are shown in Figs. 1 and 2, and some temperature monitoring data are shown in Table 1.

4.2 Simulation results

The feasibility of the IPSO in this paper is verified through simulation experiments, and the simulation results are shown in Figs. 3–5. The temperature data are predicted using the LSTM neural network based on initial data, and the results are shown in Figs. 6 and 7 and Table 2, and the re-optimization result of the wireless sensor layout scheme is shown in Figs. 8–10.

The efficiency of the IPSO is verified and evaluated by comparing it with that of the traditional

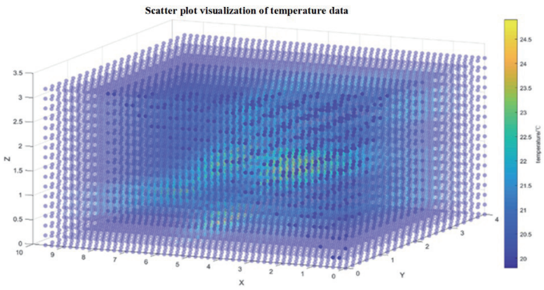


Fig. 1. (Color online) Four-dimensional scatter plot of experimental data.

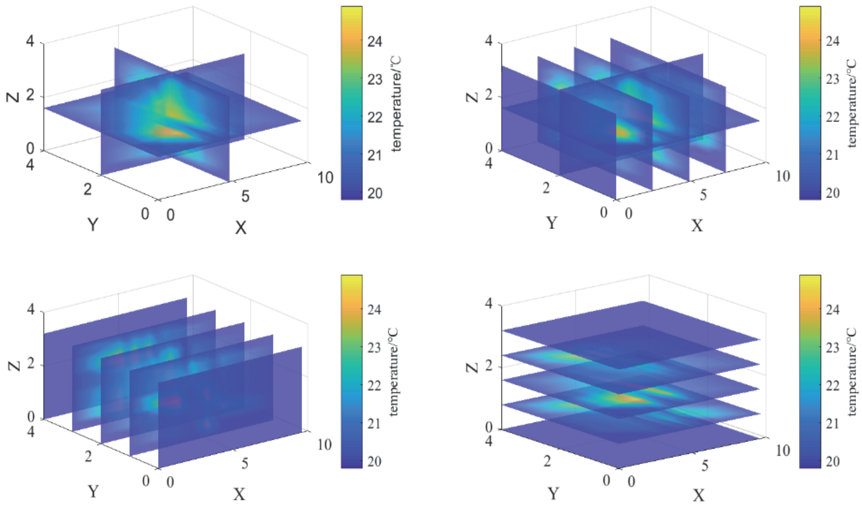


Fig. 2. (Color online) Four-dimensional slices of experimental data .

Table 1
Selected sensor temperature data

Sensor position	Temperature (℃)				
(*x*, *y*, *z*)	2021-04-25 00:05:30	2021-04-25 00:35:30	…	2021-04-30 09:35:30	2021-04-30 10:05:30
(3.2,1,0.4)	20.6	20.5	…	20.7	20.7
(3.7,1,0.4)	20.0	20.0	…	20.9	20.9
(4.2,1,0.4)	20.7	20.7	…	20.8	21.8
(4.7,1,0.4)	20.8	20.8	…	20.7	20.7
(5.2,1,0.4)	20.3	20.4	…	20.5	20.6
(5.7,1,0.4)	20.5	20.5	…	20.4	20.5
(6.2,1,0.4)	19.9	19.9	…	20.1	20.1
…	…	…	…	…	…
(3.2,3,2.2)	19.5	19.5	…	20.9	20.9
(3.7,3,2.2)	20.3	20.3	…	21.9	21.9
(4.2,3,2.2)	19.7	19.7	…	20.7	20.7
(4.7,3,2.2)	20.3	20.3	…	19.7	19.8
(5.2,3,2.2)	19.5	19.5	…	19.9	19.9
(5.7,3,2.2)	20.2	20.2	…	19.7	19.6
(6.2,3,2.2)	20.2	20.3	…	20.2	20.2

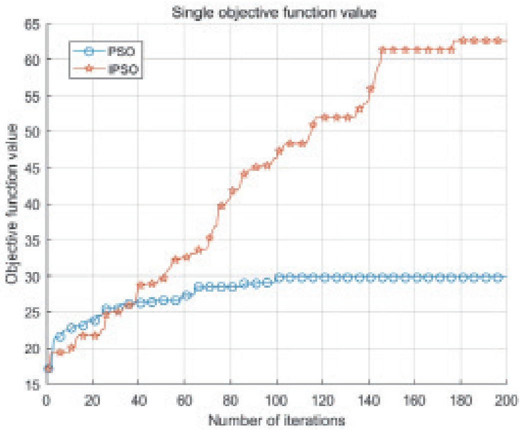


Fig. 3. (Color online) Single iterative run diagram of the objective function based on initial temperature data.

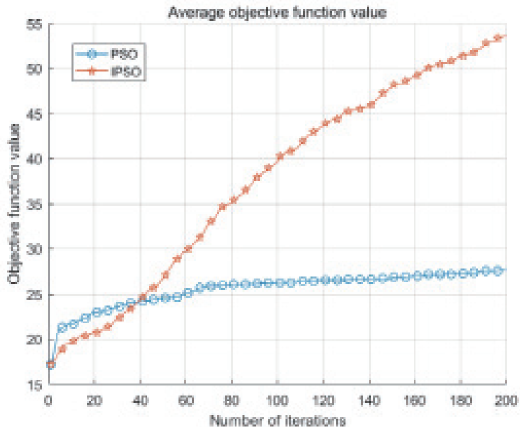


Fig. 4. (Color online) Mean iteration curve of the objective function based on the initial temperature data run 15 times.

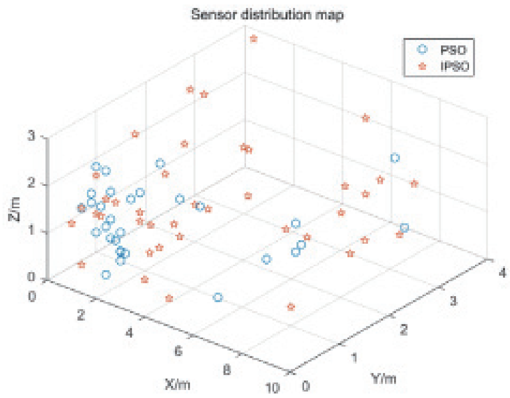


Fig. 5. (Color online) Location optimization diagram for two algorithms based on initial temperature data.

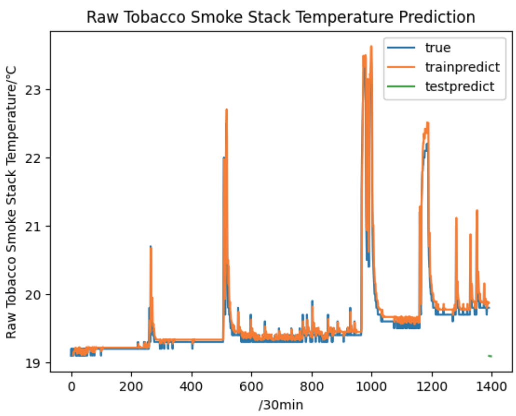


Fig. 6. (Color online) Schematic diagram of the predicted results of the edge side temperature data of the raw tobacco pallet.

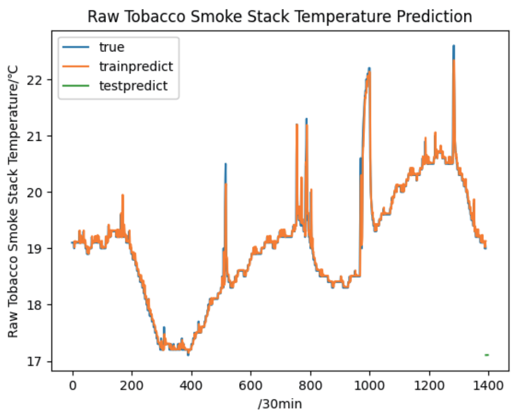


Fig. 7. (Color online) Schematic diagram of the prediction results of the temperature data at the center side of the raw tobacco pallet.

Table 2
Temperature prediction data for selected sensors.

Sensor position (x, y, z)	Predicted temperature (°C) 2021-04-30 10:35:30	2021-04-30 11:05:30	…	2021-04-30 12:35:30	2021-04-30 13:05:30
(3.2,1,0.4)	16.42	16.41	…	16.41	16.42
(3.7,1,0.4)	17.73	17.72	…	17.72	17.72
(4.2,1,0.4)	16.79	16.79	…	16.80	16.80
(4.7,1,0.4)	18.02	18.02	…	18.02	18.02
(5.2,1,0.4)	17.10	17.10	…	17.10	17.11
(5.7,1,0.4)	18.25	18.26	…	18.26	18.26
(6.2,1,0.4)	17.83	17.84	…	17.85	17.85
…	…	…	…	…	…
(3.2,3,2.2)	19.41	19.41	…	19.42	19.42
(3.7,3,2.2)	19.70	19.70	…	19.70	19.70
(4.2,3,2.2)	19.80	19.80	…	19.79	19.79
(4.7,3,2.2)	19.96	19.96	…	19.97	19.96
(5.2,3,2.2)	20.01	20.01	…	20.02	20.02
(5.7,3,2.2)	19.79	19.79	…	19.80	19.80
(6.2,3,2.2)	19.37	19.37	…	19.35	19.34

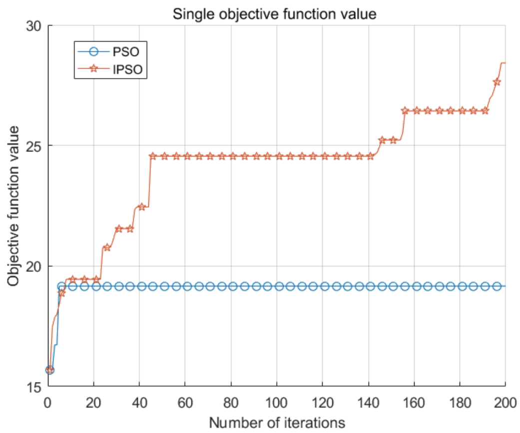


Fig. 8. (Color online). Single-run objective function iteration graph.

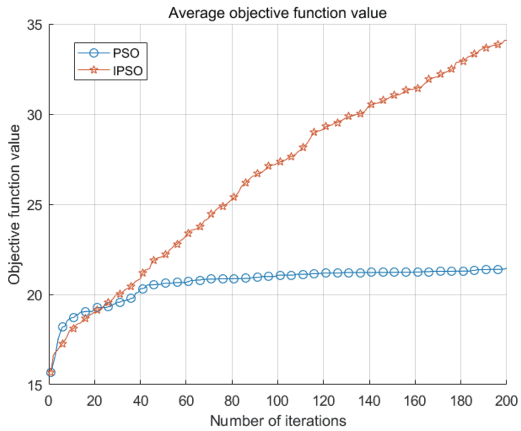


Fig. 9. (Color online) Iterative graph of the average value of the objective function for 15 runs.

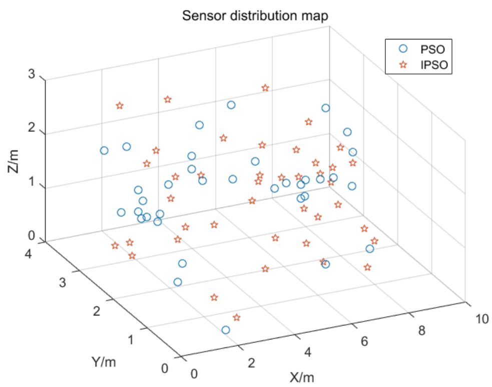


Fig. 10. (Color online) Location optimization diagram of two algorithms.

PSO, which includes the convergence rate and the optimal fitness value. The simulation results show that the IPSO has a higher ability than the traditional PSO in determining the value of the optimal fitness function and that the algorithm designed in this paper has a certain improvement in the convergence rate compared with the traditional algorithm. The algorithm designed in this study has a higher global search capability in solving such problems.

5. Conclusions

Aiming at the problems of insufficient mildew information monitoring and high equipment investment cost in the current process of curing raw tobacco leaves, in this paper, we design an IPSO to study the sensor layout optimization problem, and according to the logistics center of Hongyun Honghe Tobacco (Group) Co., Ltd., the monitoring of cigarette pallets is used as the source of experimental data to optimize the position and number of sensors in the pallets. The sensor layout optimization model built in this study is based on the actual tobacco maintenance background and considers the effect of the internal temperature of the tobacco pallet on the moldy rate. It is a further expansion of the traditional WSN problem. We further consider the effect of temperature on the raw tobacco leaves on the basis of the WSN problem. The effects of mildew and the IPSO are used to solve the model to obtain a preliminary layout plan, and then the mildew information is predicted using the LSTM neural network algorithm so as to re-optimize the preliminary sensor layout plan to account for the rationality of the sensor layout plan. The sensor layout proposed in this paper has a good reference value for tobacco companies in the management and control of mildew information in tobacco leaf maintenance, but there are still many uncertain factors in an actual application, such as the quality and moisture content of the tobacco leaves. Owing to the effects of subjective human factors such as inspection errors, sensor layout schemes under the effects of objective factors such as human factors and sudden weather conditions are also the next main research direction.

Acknowledgments

This article was supported by Hongyun Honghe Tobacco (Group) Co., Ltd. Technology Project (HYHH2019XX03, HYHH2019YL01).

References

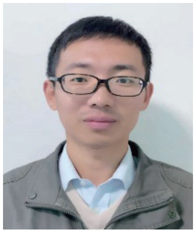
1. Y. Luo, B. Chen, F. Li, W. Zhang, J. Zhou, and X. Xu: J. Kunming University **42** (2020) 13. https://doi.org/10.14091/j.cnki.kmxyxb.2020.06.003 (in Chinese).
2 D. D. K. Rathinam, D. Surendran, A. Shilpa, A. S. Grace, and J. Sherin: 2019 5th Int. Con. Advanced Computing & Communication Systems (ICACCS) 515. https://doi.org/10.1109/ICACCS.2019.8728284
3 O. J. Pandey and R. M. Hegde: IEEE Trans. Veh. Technol. **67** (2018) 7719. https://doi.org/10.1109/TVT.2018.2839562
4 M. Elhoseny, A. Tharwat, A. Farouk, and A. E. Hassanien: IEEE Sens. Lett. **1** (2017) 1. https://doi.org/10.1109/LSENS.2017.2724846
5 L. Feng, X. Ran, G. Mei, and T. Sun: J. Information Engineering University **16** (2015) 557. https://doi.org/10.3969/j.issn.1671-0673.2015.05.008
6 X. Liu, X. Zhang, T. Hu, and Q. Zhu: Appl. Res. Comput. **35** (2018) 2063. https://doi.org/10.3969/j.issn.1001-3695.2018.07.033 (in Chinese).

7 K. Yang and K. Cho: Energies **12** (2019) 4403. https://doi.org/10.3390/en12234403
8 M. Khodabandeh, M. Saryazdi, and A. Ohadi: Proc. Inst. Mech. Eng., Part C: J. Mech. Eng. Sci. **234** (2020) 1137-1145. https://doi.org/10.1177/0954406219891756
9 M. Mohammed and R. Hasan: 2017 13th Int. Con. Intelligent Computer Communication and Processing (ICCP) (2017) 93. https://doi.org/10.1109/ICCP.2017.8116988
10 Y. Xu, Y. Yin, F. Ye, L. Ye, and R. Song: Light Ind. Sci. Technol. **36** (2020) 68 (in Chinese).
11 S. Hao, X. Zhao, and Y. Shi: J. Chinese Cereals and Oils Association **34** (2019) 64 (in Chinese).
12 H. Li, R. Qiu, Q. Dong, and D. Ye: J. Chin. Agric. Mech. **37** (2016) 78 (in Chinese). https://doi.org/10.13733/j.jcam.issn.2095-5553.2016.09.017.
13 H. Jia, S. Zhang, C. Zhu, Z. Xing, and Z. Yang: Sci-tech Innovation Prod. **4** (2018) 64 (in Chinese).
14 G. Zhao, H. Jia, S. Zhang, X. Peng, J. Li, and J. Jun: Forest Eng. **35** (2019) 61 (in Chinese). https://doi.org/10.16270/j.cnki.slgc.2019.02.010
15 H. Jin: Xidian University (2012) (in Chinese).
16 Z. Chen, J. Guo, L. Jia, and Y. Tan: J. University of Science and Technology of China **3** (2002) 54 (in Chinese).
17 Z. Chen, J. Chen, Y. Tan, P. Hu, and J. Guo: J. University of Science and Technology of China **1** (2005) 127 (in Chinese) .

About the Authors

Yueming Xu was born in Fuyuan, Yunnan province, China in 1972. He received his Ph.D. degree from Yunnan University in July 2017. From 1994 to the present, he is a general supervisor of Hongyun Honghe Tobacco (Group) Co., Ltd. His main research direction is business management.

Shiyun Chen was born in Dali, Yunnan Province, China in 2000. He is currently an undergraduate student in civil aviation of Kunming University of Science & Technology. His main research direction is artificial intelligence and intelligent systems.



Bin Chen was born in January 1986. He obtained his master's degree in control science and engineering from Shandong University in July 2011. As a section chief of Hongyun Honghe Tobacco (Group) Co., Ltd., he is mainly engaged in logistics technology management, which is his main research direction.

Jilai Zhou was born in Kunming, Yunnan Province, China in 1988. He received his master's degree in control engineering from Kunming University of Science & Technology in July 2014. He is now working for Hongyun Honghe Tobacco (Group) Co., Ltd., where he is mainly engaged in logistics technology management. His main research directions are lean management and cigarette smart manufacturing.

Renjie Xu was born in Kunming, Yunnan province, China in 1989. He received his master's degree in control engineering from Kunming University of Science & Technology in July 2017. He is now working for Hongyun Honghe Tobacco (Group) Co., Ltd., where he is mainly engaged in logistics technology management. His main research directions are warehouse logistics technology and intelligent logistics construction.

Nan Pan was born in Tongling, Anhui Province, P.R. China in 1986. He received his B. Sc. degree in 2008 from Anhui University of Science and Technology and his Ph.D. degree in 2012 from Kunming University of Science and Technology.