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Organization of an air quality monitoring model for dust-free rooms using the control chart techniques

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Recently, high-tech industries such as semiconductor, aerospace, optoelectronics, precision manufacturing precision required for its products increasingly stringent and dust-free rooms operating environment of various pollutants control requirements are also increasing. Accuracy ventilation in dust-free room is related to the experimental results, proper ventilation can help reduce levels of pollution particles inside the laboratory. In addition to particle pollution exclusion, the pollution particles into the switch through the door, whether we can be inhibited by different ventilation position pollution particles into the lab, then laboratory ventilation should be a priority. Laboratory common sources of pollution, tiny particles such as micro-electromechanical laboratory processes generated by the air conditioning ventilation equipment into dust, biological experiments may leak off bacteria, these contaminated dust particles and bacteria accumulate even off the air in the operating environment, some will direct the human body after inhalation injury, and can cause damage and affect the accuracy of the experimental laboratory equipment.

Key word: Dust-free room, pollution particles, ventilation equipment.

INTRODUCTION

Recently, product accuracy in high-tech industries, such as semiconductors, aerospace, optoelectronics, and precision manufacturing, is increasingly stringent, as well as control of various pollutants in operating environments. In this situation, dust-free rooms emerge. Although the general laboratory ventilation requirements are not higher than those in dust-free rooms, the design analysis techniques are the same. Ventilation in laboratories may affect the accuracy of experimental results, and proper ventilation can help reduce the content of polluted particles in labs. Besides discharge of polluted particles, the entry of polluted particles into labs can be prevented through different ventilation positions when lab doors are opened or closed, thus, ventilation in laboratories is very important. Pollution sources in laboratory rooms include particulates from MEMS lab processes, dust caused by air conditioning ventilation, and bacteria from biology experiments. Such polluted particles, dust, and bacteria

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may accumulate in the air of an operating environment, some of which may harm the human body after inhalation, cause damage to experiment equipment, and affect experiment accuracy.

The studies related to pollution discharged through ventilation include: the vertical inlet air system, as discussed by Qian et al. (2008) in which different air inlet and outlet positions are designed to discharge polluted particles exhaled by patients in the double sickbeds; Zhao et al. (2007) discussed factors affecting the diffusion of polluted particles in indoor environments, and simulated the discharge of polluted particles in personal ventilation rooms (Zhao et al., 2007; Memarzadeh et al., 2000) discussed the discharge of polluted particles at different ventilation rates in hospital isolation wards; Chiu (2004) discussed the impact of instantaneous loss of pressure on room airflow when personnel enter or leave a single negative pressure isolation ward when ward doors are opened; Yongson et al. (2007) analyzed airflow in air conditioned spaces; Xu et al. (2008) discussed the impact of different pollution sources; Chow et al. (2008) discussed surgical rooms; Gao et al. (2007) discussed the accumulation of polluted particles in rooms, in addition to diffusion of polluted particles; Zhang et al. (2006) also used a vertical inlet air system when discussing diffusion of polluted particles.

Workers and students spend about half their working hours at work or school. Therefore, maintaining adequate indoor air quality (IAQ) in schools and the workplace is becoming a top priority for facility managers and building operating engineers. An essential element for maintaining adequate indoor air quality is outside air to dilute indoor air pollutants and exhaust these contaminants along with moisture and odors from our buildings. Carbon dioxide is a natural component of air. The amount of CO_2 in a given air sample is commonly expressed as parts per million (ppm). The concentrations of CO_2 found in most schools and offices are well below the 5,000 ppm occupational safety standard (time weighted average for an eight-hour workday within a 40 h work week) for an industrial workplace. The most widely accepted standard is the American Society of Heating, Refrigeration, and Air Conditioning Engineers (ASHRAE) Standard 62. Some state and local codes have adopted the ASHRAE Standard 62 ventilation requirements. Tartakovsky et al. (2013) presented results of particle mass, number and size measurements inside passenger cars (PCs), vans and urban buses. Effects of the in-cabin air purifier on particle concentrations and average size inside a vehicle are studied. Use of the air purifier leads to a dramatic reduction, by 95 to 99%, in the measured ultrafine particles number concentration inside a vehicle compared with outside readings. The lowest values of particle concentrations inside a PC without air purifier were registered under the recirculation ventilation mode, but the issue of CO_2 accumulation limits the use of this mode to very short driving events.

Generally, in most studies of polluted particles in a negative pressure space, gas concentration is used to substitute the concentration of actual particles. Although most findings differ little from the actual results, polluted particles of different materials or sizes cannot be simulated. The above two parameters can affect simulation results.

This study conducted the Taguchi experiment to analyze system parameters, impact, and system performance, determines the optimal parameters of discharge outlet, and establishes a laboratory pollution discharge prediction system, as based on the neural network, in order to improve the predictive and control abilities of lab cleanliness. Through optimized engineering analysis, this study aims to determine the optimal position of discharge outlets affecting pollutions, thus, improving process quality and reducing production time through discharge system control factors and parameter levels, and establishing a pollution prediction and control system.

LITERATURE REVIEW

Taguchi experiment method

The Taguchi experiment method is to seek process parameter level combinations and ensure that product quality has minimum variations in proximity of the expected target value. In previous literature, the Taguchi experiment method was widely applied in product design and process improvement, and achieved good effect (Tong et al., 1997). Parameter design is the major step of the Taguchi experiment method, and is aimed at determining process parameters and improving process quality. Taguchi has proposed various performance measures known as Signal-to Noise (S/N) ratios for evaluating the performance of engineering systems. The greater the S/N ratio, the better the quality process. And the greater the S/N ratio, the smaller the process loss. In communications, S/N ratio denotes communication efficiency, S denotes signal, and N denotes noise. The higher the S/N ratio, the better the communication efficiency. During communication, output and power of receivers can be decomposed into signal power and noise power, which ratio can be used as the criterion for evaluating the transfer efficiency of a communication system. The S/N ratio of quality characteristics is defined, as follows:

$$SN_{\text{STB}} = -10\log_{10}(MSD) = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n}y_i^2\right)$$

(1)

Where *MSD* is the mean square error of deviation from the target value, *n* is the number of repeated tests, y_i is the observed value of the test.

$$\bar{y} = \sum y_i / n \text{ and } s^2 = \sum (y_i - y)^2 / (n-1).$$

The Dr. Yasuto Taguchi used $L_a(b^c)$ to denote the orthogonal array, where L represents the orthogonal array, as it is evolved from Latin Square, 'a' is the frequency of the experiment (orthogonal array), 'b' is the level of various factors, and 'c' is the column number of the orthogonal array. Only in this manner can the optimal parameter combination be obtained. Thus, Dr. Yasuto Taguchi used the "orthogonal array" and S/N ratio to determine optimal factor combinations (Sue, 2002). However, the Taguchi method has some disadvantages. While the Taguchi method can determine one group of better parameters from the original set parameters, most known parameters are based on information from manufacturers or engineers. The parameters set by the Taguchi method are discrete values, and cannot effectively determine the optimal parameters of continuous variables (Tong and Su, 1997).

Neural network

In recent years, the neural network has been widely used to solve data modeling in commerce, research, and engineering environments. These problems can be divided into four types: forecasting, classification, functional approximation, and data mining. It has more significant effect on machine learning, classification, and process prediction models (Wong et al., 1997). The neural network model depends on supervised learning networks, unsupervised learning networks, associate learning networks, and optimization application networks (Ye, 2001). In the past, multi-classification problems were solved by a back-propagation network (BPNN), RBFNN, and LVQ (Ibrahim et al., 2004; Kohonen et al., 1986). The back-propagation network architecture is a multilayer perceptron (MLP), and the learning algorithm often uses error back propagation for classification, diagnosis, function estimate, and prediction, and the effect is significant (Dutta and Shekhar, 1988; Sekeroglu, 2004). In addition, Radial Basis Function Neural Networks (RBFNN) has better mapping ability, and comprises the same architecture as the MLP. As it is a basic feed-forward neural network combination, it can reduce learning time.

Control chart

The control chart was developed by Dr. Shewhart in Bell Telephone Laboratories (BTL) in 1924 with the aim of monitoring process changes. Although the control chart was originally designed for the manufacturing environment, when a suitable quality measurement system is established, it can be used for different industry quality management. The control chart has multiple uses in process improvement cycles, including: (1) the test process is used for statistic control; (2) monitor whether the controlled work process has any change; (3) seek and test work process improvement opportunities.

The final goal of the statistics process control is to reduce the variance of output results by eliminating non-natural variations. After stabilization of the work, the impact of natural variations on the process can be further reduced through management, which can perfect output results and improve quality. The control chart can help infection control personnel to monitor the changes of incidences of hospital infection, while the clear and visible chart interface facilitates communication with clinical staff to promote their recognition and coordination with infection control, which can minimize the incidence rate of hospital infection.

The control chart is a tool of graphical representation used to monitor the changes of measured values of quality characteristics over time. Control chart operation is, as follows: at intervals (for example: every 0.5 h), management personnel takes one group of samples from the process, and draws the sample points on the control chart in order to judge whether the process is under a controlled state upon calculation of sample statistics. The typical control chart consists of one central line (CL) and two control lines: for the formation of the upper control line (UCL) and lower control line (LCL), the basic principle is the same as that of statistical hypothesis testing, which is based on the null hypothesis "H0: process is at a statistic control state". When the sample points fall within the control bound, the null hypothesis cannot be refused. We define the control limits on the corresponding Z chart as:

$$Z = \frac{x - \bar{x}_{t\,\text{arg}\,et}}{R_{t\,\text{arg}\,et}}$$

$$Z_{UCL} = 3$$
$$\bar{Z} = 0 \tag{2}$$
$$Z_{LCL} = -3$$

and W chart as

$$W_i = \left| Z_i - Z_{i-1} \right|$$
$$W_{UCL} = D_4$$
$$\bar{W} = 1 \tag{3}$$
$$W_{LCL} = D_3$$

The constants D_3 and D_4 are tabulated for various samples of n. The control chart is a tool of graphical representation used to monitor the changes of measured values of quality characteristics over time. Control chart operation is, as follows: at intervals (for example: every

0.5 h), management personnel takes one group of samples from the process, and draws the sample points on the control chart in order to judge whether the process is under a controlled state upon calculation of sample statistics. When the sample points fall within the control bound, the null hypothesis cannot be refused. Generally, the pollutant sources in laboratories include the particulates of the MEMS lab process, meaning dust caused by air conditioning ventilation and bacteria from biology experiments. These polluted particles may even accumulate dust into the air of the operating environment, some of which may harm the human body upon inhalation, causing damage to experiment equipment and affecting experimental accuracy. This study intends to establish one lab pollution discharge prediction system with the Taguchi neural network, improve the prediction and control abilities of lab cleanness, and predict and monitor air quality of return air inlet pollutions. It also intends that the application scope of this technology can meet the actual needs of the industry.

RESEARCH METHODS AND PROCEDURES

Through optimized engineering analysis, this study aims to determine the optimal position of discharge outlets affecting pollutions, thus, improving process quality and reducing production time through discharge system control factors and parameter levels, and establishing a pollution prediction and control system. The research method and procedures are described, as follows: (1) establish a Taguchi experiment assessment model for discharge outlets: first, establish lab pollution discharge outlet parameters and a quality assessment model, as based on the Taguchi experiment method and quality characteristic relationship model; (2) establish a pollution prediction and monitoring system.

Lab physical model

The negative pressure room model consists of the front room and the research space. The front room is 4 m long, 5 m wide, and 5 m high; the study space is 6 m long, 5 m wide, and 5 m high; the door is 1 m wide and 220 m high. In this research, the ventilation volume is set to 12ACH (air change per hour), according to the relevant specifications of negative pressure isolation wards, and the single variable air inlet position is considered. The ISO 14644 clean room classification is now the accepted worldwide standard for classifying the cleanliness of the air in clean rooms and clean zones. To test the performance of a 100 ft^2 clean zone specified as ISO Class 6. The particle concentrations were measured by a Handilaz Mini Particle Counter. The air particle counters monitor from 0.1 to 25 microns.

Taguchi experiment and data collection

Through changes of air inlet position and frequency of door opening/closing, this study discussed entry of polluted particles into wards, as well as the discharge of polluted particles within the wards. In this study, the experimental factors are 8 control factors in total, and each control factor has three levels. The experimental control factors and the levels are as listed in Table 1, and the $L_{27}(3^{13})$ orthogonal array is selected for the experiment. Each experimental level combination is tested four times. The

experimental observation values of quality features (Smaller the Better) of polluted particles are collected, and the S/N ratio of the quality features is calculated according to Equation (1), where $i = 1, 2, , 27$ is the experiment combination, and $j = 1, 2,3,4$ are the repeated observation values of each experiment combination.

Establishment of lab air quality neural prediction model

At this stage, this study uses BPNN, RBFN, and SVM classification as tools that enhance the performance of previous engineering prediction and analysis in order to establish a lab air quality neural prediction model. First, data set T is divided into training data and testing data. Crossover verification can prevent occurrence of over-fitting and accurately reflect the actual effectiveness of the system.

(i) RBFNN: RBFNN has a single hidden layer in a structure similar to a two-layer perceptron, and each neural between the input layer and hidden layer are fully connected. The main concept of RBFN is to establish many radial basis functions, and use function approximation and curve fitting to determine the mapping relationship between input and output, that is, the corresponding radial basis function $\Phi(|x - d|)$, as established in each neural of the hidden layer. Data set T contains 8 experimental factors and a number of experimental combinations $n=27$, thus, the RBFNN is a structure consisting of dimensions ($t = 8$), n inputs, k neural hidden layers, and one output value.

(ii) SVM regression prediction: Like the neural network, SVM is a non-linear prediction tool based on data. The SVM theory, as proposed by V. Vapnik, is based on structural risk minimization (SRM), which is superior to the traditional Empirical Risk Minimization (ERM). This is one of the important objectives of the statistical learning theory. SVM is mainly applied to model recognition, function approximation, probability density estimation, etc.

$$f(x) = \sum_{i=1}^{N} w_i \phi(x) + b \qquad (4)$$

In order to prevent over fitting and improve generalization of the prediction model, structural risk, and minimizing its functions, should be considered:

$$\min \quad \frac{1}{2}\|w\|_2 + C \qquad (5)$$

Where C is the generalization parameter, which differs from Vapnik's SVM, and the LS-SVM error term is defined, as follows:

$$y_i(x)[w^T \Phi(x) + b] = 1- \xi_i, \quad i =1,2, , n \qquad (6)$$

The optimal solution is:

$$\min_{w,b,\xi} \quad \varsigma(w, b,\xi) = \frac{1}{2}|w|^2 + C\sum_{i=1}^{n}\xi^2 \qquad (7)$$

s.t. $y_i(x)[w^T \Phi(x) + b] = 1- \xi_i, \quad i =1,2, , n$ and $\xi_i \geq 0$.

Dual solution of the decision function $f(x, w)$ is as shown in Equation (6):

$$y(x) = f(x, w) = sign [\sum_{i=1}^{n} \alpha_i y_i K(x, x_i) + b] \qquad (8)$$

Table 1. Experimental observation value of $L_{27}(3^{13})$ orthogonal array.

Experimental combination	A	B	C	D	E	F	G	H	y_1	y_2	y_3	y_4	SN_i	$\bar{y}_i$
									Contaminant particles					
1	1	1	1	1	1	1	1	1	-0.05208	0.341243	0.041564	0.036231	-40.2773	0.09174
2	1	1	1	1	2	2	2	2	0.411286	0.140745	0.02873	-0.07563	-40.3142	0.126283
3	1	1	1	1	3	3	3	3	0.422894	0.070002	0.08247	0.13904	-40.4853	0.178602
4	1	2	2	2	1	1	1	2	-0.45425	-0.47746	-0.28188	-0.40653	-37.8320	-0.40503
5	1	2	2	2	2	2	2	3	0.142604	-0.26078	0.089087	-0.05204	-39.6527	-0.02028
6	1	2	2	2	3	3	3	1	-0.56453	-0.40458	-0.29631	-0.50261	-37.6743	-0.44201
7	1	3	3	3	1	1	1	3	0.303426	0.078534	-0.25761	0.126816	-40.0577	0.062792
8	1	3	3	3	2	2	2	1	0.428214	0.003881	0.08247	-0.00615	-40.2808	0.127104
9	1	3	3	3	3	3	3	2	-0.41677	0.362928	0.037754	0.444637	-40.4424	0.107137
10	2	1	2	3	1	2	3	1	-0.28472	0.079067	-0.0583	0.299452	-39.9064	0.008875
11	2	1	2	3	2	3	1	2	0.092301	0.378214	-0.20227	0.139083	-40.3231	0.101832
12	2	1	2	3	3	1	2	3	0.433293	0.522544	0.229252	0.361	-41.3475	0.386522
13	2	2	3	1	1	2	3	2	-0.5239	-0.4012	-0.38775	-0.5084	-37.5883	-0.45531
14	2	2	3	1	2	3	1	3	-0.24264	-0.20835	-0.1002	-0.46207	-38.6602	-0.25332
15	2	2	3	1	3	1	2	1	-0.31858	-0.0482	0.162679	-0.17085	-39.4508	-0.09374
16	2	3	1	2	1	2	3	3	-0.14784	-0.40298	-0.11163	-0.29158	-38.6623	-0.23851
17	2	3	1	2	2	3	1	1	0.335832	0.024499	0.329713	0.437989	-40.8817	0.282008
18	2	3	1	2	3	1	2	2	0.43547	0.20189	0.612247	0.491603	-41.4617	0.435303
19	3	1	3	2	1	3	2	1	-0.05208	0.341243	0.041564	0.036231	-40.2773	0.09174
20	3	1	3	2	2	1	3	2	0.411286	0.140745	0.02873	-0.07563	-40.3142	0.126283
21	3	1	3	2	3	2	1	3	0.422894	0.070002	0.08247	0.13904	-40.4853	0.178602
22	3	2	1	3	1	3	2	2	-0.45425	-0.47746	-0.28188	-0.40653	-37.8320	-0.40503
23	3	2	1	3	2	1	3	3	0.142604	-0.26078	0.089087	-0.05204	-39.6527	-0.02028
24	3	2	1	3	3	2	1	1	-0.56453	-0.40458	-0.29631	-0.50261	-37.6743	-0.44201
25	3	3	2	1	1	3	2	3	0.303426	0.078534	-0.25761	0.126816	-40.0577	0.062792
26	3	3	2	1	2	1	3	1	0.428214	0.003881	0.08247	-0.00615	-40.2808	0.127104
27	3	3	2	1	3	2	1	2	-0.41677	0.362928	0.037754	0.444637	-40.4424	0.107137

When the above four Kernel functions are selected in solving different problems, the results obtained from SVM, as based on different parameters, may also have a difference. Thus, how to adjust SVM parameters to establish classifiers is very important. In prediction learning, sample attributes, structure, and model and parameter selection are important issues. Currently, the most used method for adjusting parameters is the Grid Algorithm (Hsu and Lin, 2002; Lin and Lin, 2003). The above methods are based on the two-class SVM, which are inherently two-class classifiers; when conducting multiclass classification with SVM, the given training set is used:

$$T = \{(x_1, y_1), (x_2, y_2),\ (x_n, y_n)\} \in (X \times Y)^n$$

Where n is the number of trained product samples. The parameter selection procedure is, as follows: (1) Punishment factor C denotes the eclectic degree between decision function complexity and wrong decision. (2) Sparsity parameter v approximates the percent of noise data in the total sample. When $v \in [0.3, 0.6]$, the model is ideal. (3) Kernal function, here the radial basis function is often used.

$$K(x, y) = \exp(-\left\|x - y\right\|^2 / 2\sigma^2)\ , \tag{9}$$

Where σ is width of the kernel function.

RESULTS AND DISCUSSION

In this study, the experiments were conducted based on different ventilation positions when lab doors are opened or closed to measure polluted particles in labs. For each experiment combination, measurement was conducted at four different time points in order to obtain experimental data $y_1 \sim y_4$, and there were 27 experimental combinations. The experimental data totaled to 108. The measured data were transformed into implementation data [-1, 1]. In addition, numerous polluted particles had the quality feature of the smaller-the-better (STB). The SN ratio of each experimental combination was

Table 2. Comparison of number of polluted particles in RMFN with RNN.

Network predict of pollutant particles		RBFN		SVM	
		Parameter	Accuracy/RMSE	Parameter	Accuracy/RMSE
SVM Vs RBFN	Model 1	$\{c_1, \sigma_1\}=\{1, 0.1\}$	0.893/0.056	$\{c_1, \sigma_1\}=\{1, 0.1\}$	**0.871/0.155**
	Model 2	$\{c_1, \sigma_2\}=\{1, 5\}$	**0.869/0.089**	$\{c_1, \sigma_2\}=\{1, 5\}$	0.882/0.056
	Model 3	$\{c_1, \sigma_3\}=\{1, 10\}$	0.962/0.023	$\{c_1, \sigma_3\}=\{1, 10\}$	0.881/0.064
	Model 4	$\{c_2, \sigma_1\}=\{10, 0.1\}$	0.963/0.006	$\{c_2, \sigma_1\}=\{10, 0.1\}$	0.891/0.063
	Model 5	$\{c_2, \sigma_2\}=\{10, 5\}$	0.963/0.016	$\{c_2, \sigma_2\}=\{10, 5\}$	0.940/0.044
	Model 6	$\{c_2, \sigma_3\}=\{10, 10\}$	0.964/0.011	$\{c_2, \sigma_3\}=\{10, 10\}$	0.944/0.019
	Model 7	$\{c_3, \sigma_1\}=\{50, 0.1\}$	0.9642/0.005	$\{c_3, \sigma_1\}=\{50, 0.1\}$	**0.955/0.014**
	Model 8	$\{c_3, \sigma_2\}=\{50, 5\}$	**0.967/0.006**	$\{c_3, \sigma_2\}=\{50, 5\}$	0.954/0.027
	Model 9	$\{c_3, \sigma_3\}=\{50, 10\}$	0.959/0.005	$\{c_3, \sigma_3\}=\{50, 10\}$	0.933/0.056

calculated according to Equation (1). After transformation, experiment data and SN_{STB} are as shown in Table 1.

In this study, the above experimental factors, data of level combination, and y_i of each experiment combination were used as the testing data set of RBFN and SVM. The experiment factors and level combinations are used as input variables, and the corresponding S/N ratio is used as the output variable. The data totaled to 27. In the network establishment experiment, 20 data were randomly selected as the training set, while the remaining data were used as the testing set to establish RBFN and SVM. Next, RMSE was used as an indicator to evaluate network performance.

RBFN and SVM parameter settings may affect network prediction results. The experimental parameters of $C =\{1, 10, 50\}$ and $\delta=\{0.1, 5, 10\}$ were used for testing. Testing of each group was conducted 10 times, with average correction rate and RMSE as summarized in Table 2. Based on the results of Table 2, it can be seen that Model 8 had the optimal test value of RBFM, and test accuracy/RMSE is 0.967 ± 0.006; while Model 2 had the worst value, with test accuracy/RMSE of 0.869 ± 0.089. The accuracy difference of the two models was 10%. In Model 8, both RMSE=0.006 and stability were relatively better. Based on the test results of the SVM network, the test value was the best in Model 7, with a test accuracy/RMSE of 0.955/0.014, and the test value was the worst in Model 1. The accuracy difference is 7.4%, and in Model 7 RMSE =0.014, with better stability. The RBFN network had the best test accuracy (0.967/0.006), which is higher than SVM (0.955/0.014), and the worst test performance of RBFN (0.869/0.089) was 0.02 lower than SVM (0.871/0.155). However, of the 9 test combinations, PBFN had 7 groups (Model 3-Model 9) that were superior to SVM's optimal test result. Overall, the RBFN network performance is better than SVM, and has good stability. Model 8 was the best among all experimental combinations.

Z-W control chart

The *Z-W* control chart is SPC in order to monitor the short run process. It is mainly used to standardize data and analyze the same quality features of products with different material codes, which are recorded in one control chart when production has small batches, and sufficient data cannot be used to estimate process parameters. The *W* control chart is an extension of the R control chart. Ordinary control chart technologies depend on huge data to estimate process parameters, such as mean value and standard deviation of process; however, in a short run process there is insufficient data to estimate process parameters. Under this production condition, the same machines or processes can be used to produce the same products with different material codes, or products of different types. In terms of the Z-W control chart feature, this study used frequency of opening the lab door, per unit time, as the number of batches, the pollutant index as an air quality indicator, and a RBFN system to predict air quality. The predicted value was transformed into an Excel file in order to establish an RBFN Z-W real-time air quality monitoring system. Based on the neural prediction network, the predicted data, and the Z-W control chart, a real time monitoring system is established to monitor the air quality of the return inlet and air quality changes (0.5 h) in the lab. Regarding control charts, the Z control chart can be used to monitor whether the air quality in the lab meets standard requirements, and a W control chart can be
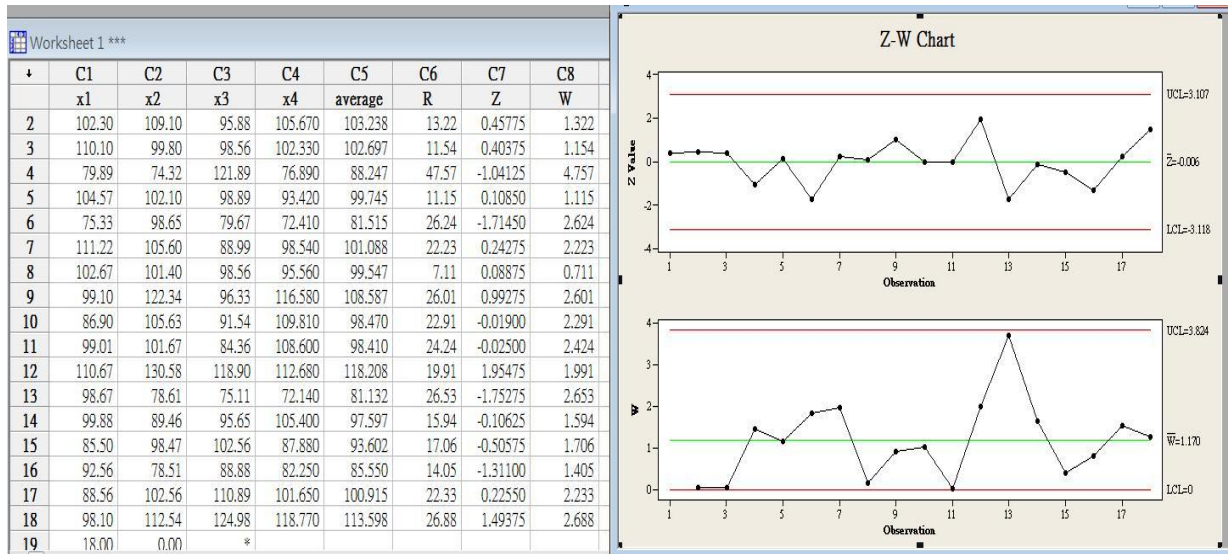
Figure 1. RBFN- ZW (0.5 h) air quality management diagram.

used to monitor the stability and changes of indoor air quality. An inlet air quality monitoring and warning system management model can reduce the work load of management personnel, improve lab quality detection levels, and establish an industry standard. In interpreting patterns on the Z chart, we must first determine whether or not the W chart is in control. Some assignable causes show up on both Z and W charts. If both the Z and W charts exhibit a nonrandom pattern, the best strategy is to eliminate the W chart assignable causes first. If one or more points fall between the warning limits and the control limits, or very close to the warning limit, we should be suspicious that the air quality process may be operating properly. The quality monitoring model of a dust-free room, as based on the neural network and control chart techniques is as shown in Figure 1.

Conclusions

In recent years, air quality management of dust-free rooms is increasingly rigorous. The Z-W control chart was often used for monitoring quality in production and manufacturing. This study established an air quality monitoring system based on neural network and Z-W control chart techniques. The main purpose is to establish a quality change monitoring method that uses the Z-W control chart production characteristics of multi-product and small batch, which method uses time as the main axis and 0.5 h as the measurement unit under indoor air quality change conditions, recorded as personnel come and go from a lab. In particular, in combination with Taguchi quality engineering, the RBFM neural network prediction system can be established after air detection is planned according to positions in the

experiment. This system can estimate a result before detection, and the predicted values are summarized into a Z-W quality management chart, through which air quality changes and tendencies can be diagnosed in advance. These findings differ from traditional ex-post detection and improvement models. Currently, industries only require prediction techniques. This model can be widely used in time-series quality change diagnosis, such as environment temperature monitoring, and environment quality changes and diagnosis.

Conflict of Interest

The authors have not declared any conflict of interest.

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