

Design of an Environmental Monitoring System for Additive Manufacturing Workshops based on Two-Level Data Fusion

Lei Wang, Gan Chen

School of Electronic Engineering, Anhui Vocational College of Electronics and Information Technology, Bengbu, China

Abstract

As an important element in the framework of intelligent manufacturing, additive manufacture works in the complex and changing workshop environment. These environments will bring great changes and instability to the data measured by every single sensor. And the traditional evaluation ways by one parameter only is limited by the one-dimensional view of it, which is not enough to get the precision that we need for the environment grade in the real time control application. In this paper, we solve these problems by giving an environmental monitoring system for the additive manufacture workshop, which is based on the dual level data fusion architecture of Kalman filtering and Bayesian networks. The system implementation is using an STM32 micro controller, aUSR-EG828 edge gateway, embedded system program, Python development environment and the Modbus communication protocol. The results of experiments show that after the first fusion stage, the temperature data has greatly decreased the fluctuation, and the data of integration is more like the actual conditions. The estimated environmental parameters are very close to the real measured ones. In particular, the mean absolute error (MAE), root mean square error (RMSE) and maximum absolute error (MAXAE) for the temperature are decreased from 0.855 °C, 0.9776 °C, and 1.7543 °C (with one sensor only) to 0.373 °C, 0.2985 °C and 0.6127 °C, respectively. Similar improvements on the noise suppression and the measure precision can also be seen for the humidity, TVOC, and PM2.5 data. The second level data fusion gets perfect accuracy on the classification of the environmental grades for all ten validation samples. In summary, the introduced framework can help to make very accurate monitoring of many parameters and a complete assessment of the environmental grades in the manufacturing environment, which can largely improve the reliability of evaluating the ambient conditions. This research provides a practical technical way for the management of environmental factors in the additive manufacturing facilities.

Keywords

Two-level Data Fusion; Kalman Filtering; Bayesian Network; Additive Manufacturing Workshop; Environmental Monitoring System.

1. Introduction

Additive manufacturing is an important element of the intelligent manufacturing framework, and it is largely promoting the deep industrial progress of the following sector [1]. The monitoring of the environmental conditions in the workshops and the assessment of the environmental classifications are important for the industrial application of additive manufacturing processes [2]. It is believed that the precise surveillance of the environmental factors in the workshops, such as the temperature, the humidity, TVOC and the PM2.5 levels, has a very important practical value for the assure of the product standards and for the protection of the workers' health [3-4]. However, in the present additive

manufacturing hall there are a lot of inaccuracy and the low reliability of the environment readings from the single sensors. Moreover, the traditional assessment approaches which are focused on the single parameter are limited by the single steady one-dimensional viewpoint and the precision of the classification of the environmental conditions are not enough [5-6]. Therefore, The development of a two tier data fusion based environmental monitoring system for additive manufacturing facilities has important theoretical and also practical engineering value in terms of the enhancement of environmental management of such kinds of workshops.

In recent years, numerous studies have been conducted on industrial workshop environmental monitoring. Some researchers have designed workshop environmental monitoring systems based on ARM microcontrollers, enabling data acquisition and monitoring of parameters including temperature, humidity, and PM2.5 [7-8]. Other studies have experimentally investigated the cumulative pollution characteristics of TVOC emitted during the collaborative operation of multiple 3D printers, providing empirical data support for TVOC pollution research [9]. Concurrently, environmental monitoring systems have been developed for specific workshop types, including welding workshops [10], textile workshops [11], and injection molding workshops [12], achieving monitoring and regulation of environmental parameters. However, in practice, relatively few studies have focused specifically on environmental monitoring for additive manufacturing workshops. As additive manufacturing constitutes an important component of intelligent manufacturing systems, environmental monitoring issues in its production workshops are becoming increasingly prominent. Consequently, there is an urgent need to establish an environmental monitoring system adapted to multi-sensor data fusion for additive manufacturing workshops, aiming to fulfill the requirements of workshop environmental monitoring and grade discrimination.

To address the above mentioned problems, in this work we present a three level architectural framework for a system, based on information collection, edge process and visual presentation, for the case of an industrial environment. We design a multi-parameter environmental monitoring system for the additive manufacturing facilities, based on a two stage's data fusion methodology. The first fusion stage is done with the use of Kalman filters and the second fusion stage is done with the use of a bayesian network. On site experiments show that the introduced system has a general benefits, as the higher accuracy in the monitoring data and a better assessment of the environmental classifications. Therefore, it is able to solve for the above mentioned shortcomings for the monitoring with the common way. This study provide a reliable technical way and a practical guide for the environmental conditions for the additive manufacturing workshops.

2. System Overall Design

2.1 System Overall Framework

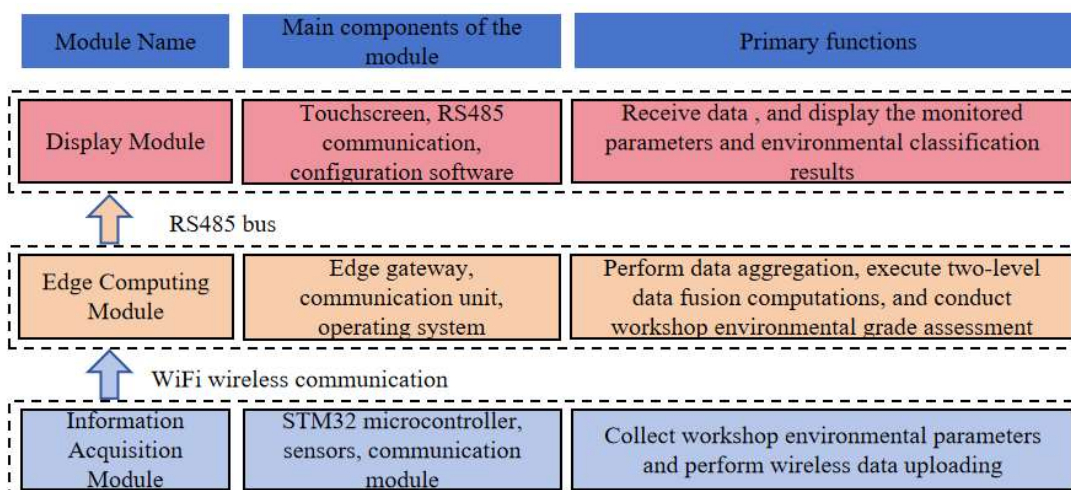


Fig. 1 The overall system architecture

The proposed environmental monitoring system for workshop are based on three parts: information collection unit, edge processing unit and visualization unit. The information collection unit is responsible for collecting the important information of the environment in the workshop, such as the temperature, the humidity, the TVOC levels and the PM2.5 concentrations, then transmit the data wirelessly. The edge processing unit is for data aggregate, do the dual-level fusion calculation and judging the environment quality rating in the workshop. The visualization unit is for receiving the data from the edge unit and output the parameters that we have monitored and the environment evaluation results on the screen. The whole system framework is shown in Fig. 1.

2.2 System Hardware Design

In the hardware architecture of the developed workshop environmental monitoring system, the data collection unit is basically consisted of a centered microcontroller, a bunch of different sensors, and a wireless communication part. The edge processing unit uses the edge gateway to perform two-stage data fusion and environmental condition assessment. A display unit is used to show the monitored data and the classification result by a touch screen. The details are described below.

(1) Microcontroller Design. STM32F103 is the microcontroller as the central processing unit. It is based on the ARM Cortex-M3 architecture. The core clock speed of the controller is 72 Mhz. This controller communicate with the sensors for temperature, humidity, TVOC and PM2.5 by TTL serial protocols. It also communicates with the communication module by the tUSART serial port to transfer the data.

(2) Sensor Selection. The system also contains the LH-TH2002 for measuring temperature and humidity, the 4R-PID for detecting TVOC, and the SDS026-F for monitoring the PM2.5 concentration. The technical specifications and the performance of the three sensor models are listed in full in Table 1.

Table 1. Sensor selection and performance parameters

Sensor Name	Measurement Range	Accuracy
LH-TH2002 temperature and humidity sensor	-40~80 °C	±0.5°C
	0~100% RH	±3%RH
LH-TH2002 temperature and humidity sensor	0-100ppm	≤±2%
SDS026-F PM _{2.5} particulate matter sensor	0.0~20.0mg/m ³	±10%

(3) Wireless Communication Module Design. The ESP8266 Wi-Fi module is chosen to satisfy the requirement of sending the collected environmental data wirelessly to the edge computing layer. The module is powered by a 3.3 V DC source. It works on the public frequency spectrum of 2.4GHz. It supports the IEEE 802.11 b/g/n wireless protocols, there is a processing unit inside this module, and it has a standard TTL serial port interface. We use a direct USART serial connection to exchange data with STM32F103 microcontroller.

(4) Hardware Configuration of the Edge Computing Unit. The Jinan USR-EG828 edge gateway is the core processing component of the edge computing unit. The processor of the gateway is Rockchip RK3568, which is a quad-core 64-bit Cortex-A53 design, with a clock speed of 2.0 GHz. There are 4 GB high-performance DDR4 RAM and 32 GB eMMC high-speed flash storage for the system. After two-stage data fusion and the environment analysis, the device sends the information and the result of classification to the display unit. The transmission is realized with RS485 bus and follows the communication standard of Modbus RTU.

(5) Display Module Design. The TPC7062Ti touch screen from Kunlun Tongtai is selected as the display unit. The unit is built on an ARM Cortex-A8 processor with clock speed of 600 MHz. It has

128 MB RAM and 128 MB flash, and the unit is low energy used. The unit can show the live data of workshop environmental conditions and the work state of the system.

2.3 System Software Design

(1) Information Acquisition Software Design. The structure of the software for information collection is design of the main loop. The development is in the Keil MDK-ARM embedded development platform. When the system is powered up or reset, the software is running for initialization and configuration. Then, It deals with the preprocessing of the raw data that has got first and pack the data. The data pack is sent to the edge gateway with the Wi-Fi communication module. After that, the data is transferred to the edge gateway, the system waits for the delay time as set by the set sampling interval before run the next data collection iteration. The operation sequence of information collection is shown in the Fig. 2.

(2) Edge Gateway Software Design. The edge gateway software is developed based on the Ubuntu 20.04 operating system and adopts a main-loop architecture. Program development and functional deployment are implemented using the Python programming language. The workflow is as follows. After the edge gateway system starts, it automatically completes initialization. It then receives the data uploaded by the information acquisition module, performs data validation and parsing, and subsequently executes the two-level data fusion algorithm. Upon completing the fusion computation of workshop environmental parameters, the system determines the environmental state based on preset thresholds, encapsulates the results, and transmits them to the display module for real-time visualization of field data and assessment outcomes. The system then enters a delay period according to the preset working cycle and proceeds to the next cycle of data reception and processing. The software workflow of the edge gateway is shown in Fig. 3.

(3) Display Module Software Design. The display module software is developed using the MCGS configuration environment. A main-loop polling architecture is adopted to achieve data interaction and visualization.

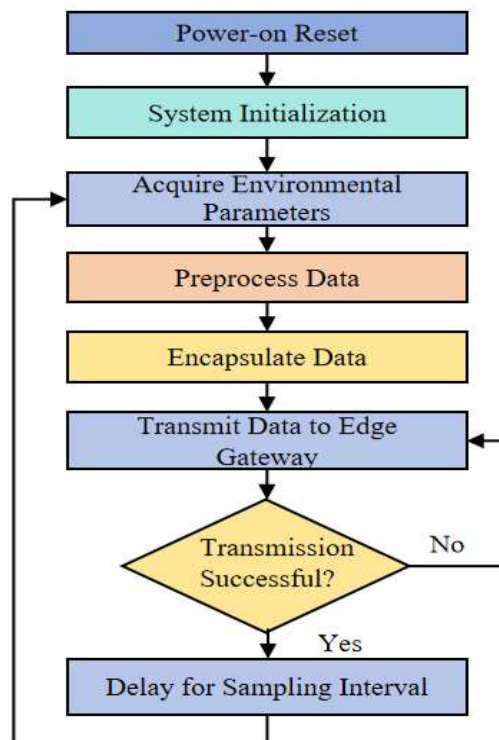


Fig. 2 Information acquisition workflow

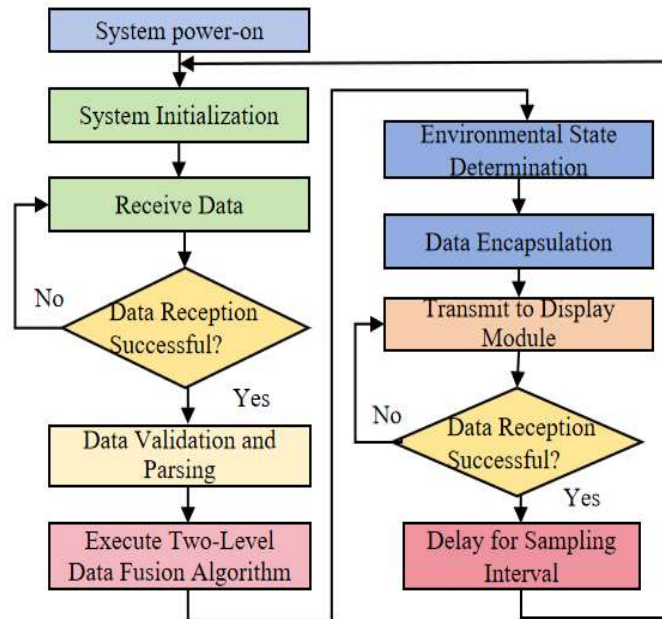


Fig. 3 Software workflow of the edge gateway

3. Construction of the Secondary-Level Data Fusion Model

3.1 Data Fusion

In this study, a two-level progressive data fusion architecture is adopted. The primary-level data fusion employs the Kalman filtering algorithm [13-14] to perform noise reduction on the monitoring data, while the secondary-level data fusion, based on a Bayesian network [15-16], enables optimized data fusion analysis and workshop environmental state determination.

(1) Primary-Level Fusion. In the primary-level data fusion, Kalman filtering is used to perform dynamic filtering and optimal estimation for random disturbance noise present in workshop environmental monitoring data, including temperature, humidity, TVOC concentration, and PM_{2.5} levels. The core model of this algorithm consists of a prediction state equation and an observation equation, as formulated below:

The prediction state equation is given as follows:

$$\hat{x}_k = A_k \cdot x_{k-1} + B_k \cdot u_k + W_k$$

where x_k is the state vector at time k , A_k is the state transition matrix, B_k is the control input matrix, u_k is the system control input at time k , and W_k denotes the process Bnoise.

The observation equation is expressed as follows:

$$Z_k = H_k \cdot x_k + V_k$$

Where Z_k is the measurement value at time k , H_k is the observation matrix, and V_k is the measurement noise of the system.

After obtaining new monitoring data, the Kalman gain is calculated by comparing the predicted state with the new measurement data, along with the observation matrix and the observation noise covariance. This gain is then used to correct the predicted state in order to obtain the optimal state estimate.

The predicted state covariance equation is expressed as follows:

$$\hat{p}_k = A_k \cdot P_{k-1} \cdot k_T^A + Q_k$$

Where \hat{p}_k is the predicted state covariance, and Q_k is the process noise covariance. The kalman gain equation is given as follows:

$$K_k = \hat{p}_k \cdot k_T^H \cdot (H_k \cdot P_k \cdot k_T^H \cdot R_k)^{-1}$$

The updated state estimation equation is given as follows:

$$x_k = \hat{x}_k + K_k \cdot (Z_k - H_k \cdot \hat{x}_k)$$

The updated state covariance equation is given as follows:

$$P_k = (I - K_k \cdot H_k) \cdot \hat{p}_k$$

Where P_k is the state covariance matrix at time k , and I represents the identity matrix.

Considering the air circulation within the workshop and the heat exchange characteristics with the external environment, the process noise W_k in the Kalman filter cannot be neglected in this scenario. Based on the above environmental characteristics and the adaptation requirements of the filtering model, the parameters of the Kalman filter are set as follows. The state transition matrix and the observation matrix are both set to unity, i.e., $A_k = H_k = 1$; the control input matrix $B_k=1$. The initial state value x_0 is taken as the initial reading of each sensor's monitoring data. The measurement noise covariance is determined according to the accuracy specifications provided in the sensor technical datasheets, while the process noise covariance is dynamically adjusted based on real-time calculation of the filtering output residuals.

(2) Secondary-Level Fusion. In this study, the Bayesian network algorithm is employed to perform secondary-level data fusion on the data preprocessed by Kalman filtering. This algorithm is grounded in probability theory and relies on a directed acyclic graph to enable reasoning under uncertainty. The workshop environmental monitoring parameters optimized by Kalman filtering—namely temperature (T), humidity (H), TVOC concentration (V), and PM_{2.5} concentration (D)—are selected as input variables. The comprehensive workshop environmental state decision output node (S) is defined and classified into three operational statuses: normal, mildly abnormal, and severely abnormal.

Under the assumption of conditional independence among the evidence nodes and based on Bayesian inference rules, the posterior probability calculation formula for each workshop environmental state, given all monitoring parameters, is derived as follows:

$$P(S \setminus T, H, V, D) = \frac{P(T \setminus S)P(H \setminus S)P(V \setminus S)P(D \setminus S)P(S)}{P(T, H, V, D)}$$

where $P(S)$ denotes the prior probability of each workshop environmental operational state, which is derived from statistical fitting of long-term historical monitoring data; The terms $P(T \setminus S)$, $P(H \setminus S)$, $P(V \setminus S)$, and $P(D \setminus S)$ represent the conditional probabilities corresponding to temperature, humidity, TVOC concentration, and PM_{2.5} concentration, respectively. These conditional probabilities are determined by constructing a conditional probability table (CPT) trained on the

sample data; $P(T, H, V, D)$ represents the joint marginal probability of the multiple monitored parameters and serves as a fixed constant during probabilistic inference within the same scenario.

In this study, the maximum a posteriori (MAP) criterion is adopted to determine the final environmental state. The state with the highest posterior probability is selected as the current actual operational state of the workshop. The decision expression is as follows:

$$s^{\wedge} = \arg \max S \in \{S_1, S_2, S_3\} P(S \setminus T, H, V, D)$$

Where s^{\wedge} denotes the environmental state determination result output by the model.

3.2 Experimental Standards and Basis

The performance of the proposed system was checked at the production site of Jiangsu Miracle Intelligent Manufacturing Technology Co., Ltd., in Suzhou, China. The site has area about 60 square meters, with six 3D printing machines. They are put in two lines that are parallel to each other with about 2.0 meter gap between two adjacent printing machines. As shown in the *Sampling specification for monitoring of hazardous substances in workplace air* [17] (GBZ 1592004) about the place of monitoring station and the elevation for sampling, three kinds of data collection station are set. One is at the center of the printer group, other is at the operator's workstation and the other one is at the air of vent. At every station, a sensor for temperature and humidity, a sensor of Total Volatile Organic Compounds (TVOC) and a sensor of PM2.5 particulate are put at 1.5 meters above the ground. A Testo 175H1 temperature and humidity meter, an ST8306 TVOC detector, and an OSENPM2.5 monitor were used as reference instruments to provide groundtruth data for validating the twolevel data fusion performance.

In this study, temperature and humidity parameters were set in accordance with the Hygienic standard for the design of industrial enterprises [18] (GBZ 12010), while the concentration limits for TVOC and PM2.5 were determined by referring to the Indoor air quality standard [19] (GB/T 188832022) and the enterprise's internal workshop environmental control criteria. The specific environmental control targets were established as follows: temperature 20–26 °C, relative humidity 40–60 %RH, TVOC $\leq 0.6 \text{ mg/m}^3$, and PM2.5 $\leq 50 \text{ }\mu\text{g/m}^3$. Considering the fluctuation characteristics of actual production conditions, the workshop environmental status was classified into three levels: normal, mildly abnormal, and severely abnormal, as detailed in Table 2.

Table 2. Classification of workshop environmental levels

Group No.	Temperature T/ °C	Relative Humidity H/ %RH	TVOC V/(mg/m ³)	PM _{2.5} D/(μg/m ³)
Normal	20–26	40–60	≤ 0.6	≤ 50
Mildly Abnorma	18–20 or 26–28	35–40 or 60–65	0.6–0.8	50–75
Severely Abnorma	<18 or >28	<35 or >65	>0.8	>75

4. Experimental Results and Analysis

4.1 Performance of Primary-Level Data Fusion

In this work, three different ways of comparison have been carried out. The first way is with the use of the measurements done by a single sensor located in the middle of the printer array. The second way is with data fused by a Kalman filter algorithm. The third is the benchmark, with the readings from a pre-calibrated reference device. The data gathering has been done in a two hours long time 10:00 to 12:00 in a common work day, and it is in a phase of the working conditions of the facility which is stable. We took measurements each two minutes, so we have sixty data points. We use these

points to draw the dynamical patterns of the fluctuation of the environmental conditions. In Fig. 4, as an example of the first data fusion process, we show the temperature data from the workshop.

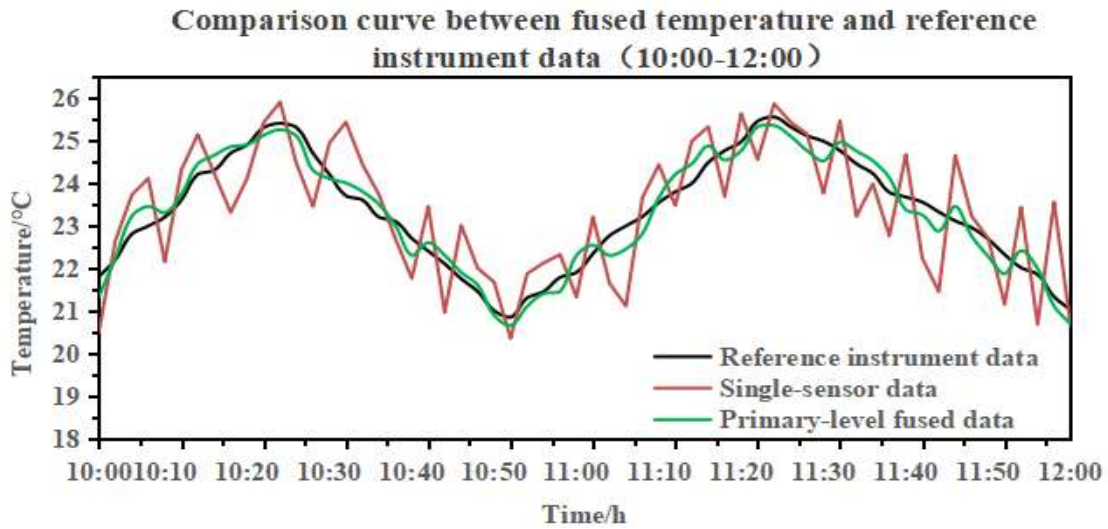


Fig. 4 Performance of primary-level fusion for workshop temperature

From Fig. 4, we see that the temperature data after the Kalman filter process (green line) is a smoother trace than the raw data of one sensor (orange line). And it also coincides more with the temperature of the benchmark that is collected by the reference instrument (black line). Therefore, the data of the first level fused really reduce the influence of the noise and give a more faithful data of the real environment.

The monitoring data set employed in this investigation is of 24 hours. The readings from the calibrated reference instrument are used as the reference of accuracy. Three criteria are used to evaluate the fusion performance: mean absolute error (MAE), root mean square error (RMSE) and maximum absolute error (MAXAE). The effectiveness of the data fusion at the primary level is shown in Table 3, taking the workshop temperature data for a specific case.

Table 3. Performance comparison of primary-level fusion for workshop temperature

Data Type	Mean Absolute Error (MAE) / °C	Root Mean Square Error (RMSE) / °C	Maximum Absolute Error (MaxAE) / °C
Single-sensor measurement data	0.855±0.062	0.9776	1.7543
Primary-level fused data	0.373±0.025	0.2985	0.6127
Reference instrument data	—	—	—

As listed in Table 3, the mean absolute error (MAE) for the data fused at the primary level is 0.373 °C, which is much less than the 0.855 °C for the data of the original measure from one and the data of the original measure from each sensor. This implies the total measurement inaccuracy is reduced very much. Moreover, the error results of various experimental runs are more steady and reliable. Comparing with the data of one sensor, the root mean square error (RMSE) and the maximum absolute error (MAXAE) for the data of the fused at the primary level is 0.2985 °C and 0.6127 °C,

respectively. These results prove that the method of Kalman filtering is able to reduce the random noise and irregular change very well and the severe measurement error is also reduced. The standard deviation for the data of fused set is 0.7437 °C, which is less 0.3697 °C than the 1.1134 °C of the standard deviation for the data of the single sensor. This finding indicates that the primary-level fused data are generally consistent with the actual fluctuation pattern of the ambient temperature and more closely reflect the on-site working conditions.

Moreover, the same primary-level fusion method obtains similar noise reduction and better estimation result for the parameters of relative humidity, TVOC and PM2.5. Finally, the primary-level data fusion algorithm achieved in this paper can reduce the monitoring error of the environmental parameters, improve the total precision of the measurement and increase the reliability of the monitoring data.

4.2 Evaluation of Secondary-Level Data Fusion

In this study, 100 data samples are collected with four environmental variables in each sample, which are the temperature, the relative humidity, the TVOC and the PM2.5 concentrations. The raw data points are firstly processed by a simple Kalman filter. 90 samples out of the total samples are used for the model training and 10 samples are used for the test. The other measurements that are taken by a certified reference instrument are the actual ground truth of each parameter. According to the three level classification that we have established during the design, which is the normal, the mildly abnormal and the severely abnormal, every one of the 100 samples has a environmental category assigned manually. The 90 annotated training samples are used to build the Bayesian network model, and a set of probabilistic reasoning rules is extracted from the model. Then, the 10 test samples are put into the trained Bayesian network to do the probabilistic inference, to assign the environmental grades automatically. The correctness of the grade assignment is checked by comparing the network outputs with the manually annotated ground truth labels, thus verifying the effectiveness of the secondary-level Bayesian network data fusion. These results are listed in Table 4.

Table 4. temperatureSecondary-level fusion results for workshop environment

Group No.	Temperature / °C	Relative Humidity / %RH	TVOC/(mg/m ³)	PM _{2.5} /(µg/m ³)	Grade Determined	Manually Labeled Grade
1	23.2	54.3	0.41	45.3	Normal	Normal
2	24.4	63.1	0.53	55.6	Mildly Abnormal	Mildly Abnormal
3	22.9	48.5	0.67	45.7	Mildly Abnormal	Mildly Abnormal
4	25.3	51.8	0.45	39.2	Normal	Normal
5	22.7	55.6	0.52	47.3	Normal	Normal
6	23.4	46.9	0.44	43.6	Normal	Normal
7	28.3	39.6	0.54	39.7	Severely Abnormal	Severely Abnormal
8	25.1	49.6	0.39	41.6	Normal	Normal
9	22.5	42.4	0.56	38.5	Normal	Normal
10	24.2	53.3	0.66	44.9	Mildly Abnormal	Mildly Abnormal

As shown in Table 4, the classification results from the second level data fusion model with the Bayesian network is the same as the environmental ratings given by the ground truth measurements of the standard reference instrument for the ten test samples. This result proves that the introduced secondary level data fusion method with the Bayesian networks is able to classify the environmental grades exactly in different working situations in the workshop. Thus, it meets the real needs of the environment assessment and the management in the additive manufacturing workshop.

5. Conclusion

The system always runs the work of the collection of the environmental data, the transfer of the data, the processing of the data, and the display of the result of the data, which meets the requirement for the regular in-situ monitoring in the circumstance of the industrial workshop. It improves the accuracy and the reliability of the first time monitoring data a lot, and it provides the strong support to the later data integration. By analyzing the relations of the different environmental factors, the system does the condition assessment, and it solves the limitation of the forward method which use to assess only one parameter.

In the dual-level integration architecture the data refinement is done by using Kalman filtering techniques and the evaluation is done by using Bayesian networks, exploiting in a synergic way advantages of both, to obtain the monitoring of a multiple parameters with a precise monitoring and a good classification of the environment. This methodology is a good technical reference to obtain a complex management of the environment and to evaluate the conditions of production in the additive manufacturing plant.

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