A Triple-Correlation Framework for Demonstrating an Innovative Gas Warning System: A Case Study in China

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Case study

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Abstract

This research aims to develop an innovative gas warning system for improving production safety in the underground coal mining industry. Coal mining is an important sector for China's economic development; gas monitoring systems are widely adopted as almost 60% of coal mining accidents are caused by gas. Existing gas monitoring systems mainly focus on simply detecting real-time data obtained from gas sensors. The literature review did not find gas monitoring systems that provide alarms or warnings from the correlation of gas with data from other sensors. This research aims to fill this gap to uncover hidden patterns and correlations between gas and temperature, wind, and dust, and incorporate data analytics into developing an innovative, integrated gas warning system. Correlational research was adopted using 328,320 data outputs obtained from ZhongXing Co. Ltd in Dec 2019. The study found strong relations between gas and temperature, wind, and dust. A Triple-Correlation Theoretical Framework and a Unified Modeling Language (UML) model were developed for an innovative gas warning system. As a result of this research, the ZhongXing Innovative Gas Warning System was developed and deployed for user acceptance testing on 28 Aug 2020.

1. Introduction

The underground coal mining industry is an important sector for China's economic development. The proportion of coal in China's energy consumption is approximately 62% in 2020 and is expected to be 55% by 2030 (Xie et al., 2019, p.169). Most coal seams are now deep and require underground coal mining that currently accounts for about 60% of world coal production (Priyadarsini et al., 2018, p.1). Underground coal mining has hazards of roof collapse, falling rocks in high-stress mines, release, and explosions of gas (Priyadarsini et al., 2018, p.1). Methane gas explosion or ignition in an underground mine is an ever-present risk (Tutak & Brodny 2019, p.1). Almost 60% of coal mine accidents are caused by gas (Shen et al. 2017, p.1, Li, Zhian & Zhang 2018, p.1) when the gas concentration exceeds limits (Zhang et al., 2020, p.1).

Gas monitoring systems are adopted widely to reduce risks of gas exceeding concentration limits in China's coal mining industry (Li, Jiang & Zhang 2018). China's State Administration of Work Safety regulations requires a monitoring system to alert the emergency response team if the gas concentration is more than the limit (Xia, Chen & Wei 2018, p.4). In practice, existing gas monitoring systems mainly focus on simply detecting real-time data obtained from methane gas sensors – (called gas data in this research). If the gas data outputs reach the threshold limit values (TLVs), the gas monitoring system will provide alarms or warnings to the safety-responsive team. Since gas monitoring systems were deployed in China's coal mine industry, the gas accidents have decreased from 492 in 2004 to 39 in 2016 (Lu et al. 2018, pp.2653-2654).

Even small gas accidents can trigger explosions resulting in injury or loss of life and damage mine tunnels, mine shafts, and expensive equipment (Cheng 2018). Underground coal exploitation is a high-risk industry linked with methane gas hazards (Tutak & Brodny 2019, p.1). Early warning systems can play a crucial role in avoiding gas accidents (Zhao et al. 2020, p.1981) and need to be continually improved and deployed in coal mining (Jo, Khan & Javaid 2019, p.183). Some systems monitor temperature sensors, wind sensors, dust sensors, etc. are communicated to gas monitoring systems; however, these are not included in the risk analysis. Current research mainly focuses on the prediction algorithms and prediction methods of gas emissions and gas concentration (Ma & Zhu 2016, p.1). There is a lack of gas monitoring systems to provide alarms or warnings triggered by any anomaly detected from the correlation analysis of gas data and data acquisition from other sensors.

This research explored whether a correlation exists between data outputs from the gas sensors and other data outputs from different sensors. Anomaly data detected from temperature, wind, and dust might be related to gas data anomaly results. This research fills this gap to uncover hidden patterns and correlations between gas and temperature, wind, and dust, and incorporate data analytics into analytics portfolios for developing the innovation gas warning system. The correlation research method was adopted in this research. The following section focuses on the literature review. The research framework and research methodology are then presented, followed by data collection and data analysis details. A Triple-Correlation Theoretical Framework and an innovative gas warning system concept is proposed.

2. Current Gas Monitoring System And Literature Review

2.1 Current Gas Monitoring System: A Case Study in China

This research focused on Mine No.1209 coal mining working-face at Shanxi Fenxi Mining ZhongXing Coal Industry Co. Ltd (ZhongXing) - a large coal company in China. The ZhongXing gas monitoring system monitors gas, temperature, wind, dust, etc. (Fig.1). If gas data are normal, the data outputs are forwarded to the monitoring system. If the data outputs of gas reach the TLVs, the alarm system will immediately alert the safety-responsive team. Other data outputs of temperature, wind, and dust are also available to be communicated to the monitoring system. However, the current gas monitoring system does not include any risk analysis potentially impacted by other outputs, such as temperature sensors, wind sensors, and dust sensors.

2.2 Literature Review

A literature review was conducted to understand the state of research into gas monitoring systems and early warning systems in underground coal mining. The literature focuses on both international research and Chinese research in English and Chinese.

This research first reviewed the literature published between 2016 and 2020 in Scopus. The search terms were “gas,” “coal mine,” “monitoring system/model/framework,” “alarming system /model/framework,” “warning system/model/framework,” “prediction system/model/ framework.” 188 papers were found. After reviewing the abstracts, most were found to focus on analyzing gas data to explore the methods and framework for providing quick responses or early warnings on any anomaly detected from gas data. A few correlational pieces of research focused on the correlation between the data obtained from different types of sensors but did not conduct any correlational analysis. Jo, Khan & Javaid (2019, p.190) conducted correlational research between temperature, humidity, gas, and CO_2 in underground coal mines and found a strong correlation between temperature and humidity. Zhao et al. (2020, p.1982) discussed gas geology, mining effects, daily prediction, mining pressure, and gas emission dynamic analysis systems. Wang, Li & Li (2019, p.1722) found that coal seam depth, coal seam thickness, temperature, and gas concentration impacted historical monitoring data on gas prediction. Xie et al. (2018, p.170) focused on 45 coal and gas outburst accidents between 1984 and 2009 in Pingdingshan No.8 mine China. They explored geological factors, coal structure factors, operation factors, and gas factors, including absolute gas emission, gas concentration, and gas release initial velocity. The analysis results showed that the soft and fallen coal seam's most sensitive factors, soft layer thickness variation, change of coal thickness, coal seam thickness, and geological structure but not explore any correlation analysis of gas factors and temperature, wind, and dust. Ma & Dai (2017, p.93) developed a warning index system for coal mine safety based on safety management, facility performance, behavior Monitor, and emergency rescue.

This research also reviewed the literature published in the core journals indexed in the Chinese science citation Index (CSCI) and the Chinese social sciences Citation Index (CSSCI) scientific database from the China Academic Journals full-text database-called China National Knowledge Infrastructure (CNKI). CNKI is the largest, continuously updated Chinese journal database globally and was released in June 1999 (CNKI 2019). The search was also limited to papers published between 2016 and 2020. The search terms were the same as for Scopus. 4590 publications were found. After reviewing the abstracts, current research in China focused on alarms to avoid exceeding the limit value of gas concentration.

Overall, there appears to be a gap in research on conducting correlational analysis to provide alarms or warnings by anomaly data detected between gas and temperature, wind, and dust.

3. Research Framework And Research Methodology

3.1 Research Framework

This research focused on Mine No.1209 in ZhongXing 19 sensors were installed, including ten gas sensors, five temperature sensors, three wind sensors, and one dust sensor (Fig.2). Table 1 shows the codes of the sensors used in this research.

Table 1
Code of Sensors

No.	Type	Sensor Name	Code	No.	Type	Sensor Name	Code
1	Gas sensor	Coal Bin T	Gas 1	11	Temperature Sensor	Working Face WD	Temp 1
2		Transport Lane T	Gas 2	12		Upper Corner WD	Temp 2
3		Working Face T	Gas 3	13		1000m Refuge WD	Temp 3
4		Upper Corner T	Gas 4	14		500m Refuge WD	Temp 4
5		Material Lane T	Gas 5	15		Wind-back Lane WD	Temp 5
6		1000m Refuge Chambers T	Gas 6	16	Wind Sensor	Transport Lane FS	Wind 1
7		middle of Wind-back Lane T	Gas 7	17		Material Lane FS	Wind 2
8		500m Refuge Chambers T	Gas 8	18		Wind-back Lane FS	Wind 3
9		Wind-back Lane T	Gas 9	19	Dust Sensor	Wind-back Lane FC	Dust
10		Wind-back Lane Mixing T	Gas 10				

The research framework focused on the correlation between gas data and data acquisition from temperature sensors, wind sensors, and dust sensors (Fig.3). Data changes from temperature, wind, and dust might be critical factors to predict the anomaly gas shift data.

3.2 Research Methodology

Reliability and validity analysis were separately conducted between gas and temperature, gas and wind, and gas and dust. The correlation analysis will then be performed between gas and temperature, gas and wind data, and gas and dust. As a quantitative research method, correlational research can inform causal inferences and, thus, evidence-based practice (Thompson et al. 2005, p.182). Correlational research does not provide the best evidence regarding causal mechanisms between two variables but indicates that either two variables are influenced by a common underlying mechanism (Messerli 2012, p.1563). Researchers may describe the strength and direction of the relationship between two variables (Paul et al. 2020), and then subject to experimental study (Thompson et al. 2005, p.182, p.190).

4. Data Collection And Data Analysis

4.1 Data Collection

Several statistical significance levels have been accepted for hypothesis testing, including 0.05, 0.01, and 0.001 (Wu, Jewell & Gide, 2012, p.8). Many authors or readers consider P values of 0.05 as the ‘gold standard’ of ‘significance’ (Nahm 2017, p.242). The smaller the significance value, the lower the risk of rejecting the null hypothesis when it is true, however, this needs to be balanced by the risk of accepting the null hypothesis when it is not true (Malhotra et al. 2006, p.581). This research adopted the value of 0.01 as the cut-off for the significance level to lower the risk of rejecting the null hypothesis.

The data obtained from a single sensor was every 15 seconds. The data outputs from each sensor per year are 2,102,400. Using a sample size calculator (Creative Research Systems 2012) at a significance level of 0.01, for the testing hypothesis of one-year data outputs, the sample size should not be less than 16,510 data outputs. This research initially obtained 15.975 data outputs between 00:00:00 am on 16 Dec 2019 and 23:59:59 on 18 Dec 2019 and less than 16.510. It kept on collecting the data until 5:31:00 am on 19 Dec 2019. Thus, 17,280 data outputs were obtained, and more than the required testing sample size (16,510). Finally, 328,320 data outputs were obtained from 19 sensors. The time series of the data outputs of 19 sensors show the visible correlations between data obtained from gas sensors, temperature sensors, wind sensors, and dust sensors except the wind 3 (highlighted in Appendix 1). The testing was followed to identify whether these visible correlations should be accepted or rejected.

4.2 Reliability Analysis and Validity Analysis

In the test of data obtained between gas and temperature, the results indicated strong evidence of meeting both the reliability and validity standards of exploratory research are listed in Table 2. Cronbach's Alpha was 0.896 and was considered to have very good reliability (above 0.8). In the test of the validity, the ratio of the number of cases to variables was 1152:1 (greater than 5:1), Kaiser-Meyer-Olkin (KMO) was 0.867 and considered to have a very good measure (great than 0.8), Bartlett's test of sphericity was 0.000 ($p<0.001$), the average communality was 0.809 (greater than 0.6). No two-item values are correlated above 0.75 (satisfied with discriminant validity).

Table 2
eliability and Validity Analysis of Gas Data and Temperature Data

Descriptive Statistics				Communalities		Cronbach's Alpha if Item Deleted	Cronbach's Alpha	KMO and Bartlett's Test		
	Mean	Std. Deviation	Analysis N	Initial	Extraction					
Gas 1	.0732	.02044	17280	1.000	.905	.587	.896	Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.867
Gas 2	.0988	.02883	17280	1.000	.886	.584				
Gas 3	.1143	.03061	17280	1.000	.851	.583				
Gas 4	.1304	.03163	17280	1.000	.840	.583				
Gas 5	.0320	.01024	17280	1.000	.774	.589				
Gas 6	.2455	.04197	17280	1.000	.900	.579				
Gas 7	.2718	.04402	17280	1.000	.924	.578				
Gas 8	.3352	.04457	17280	1.000	.863	.579				
Gas 9	.3257	.04657	17280	1.000	.927	.578				
Gas 10	.2521	.03325	17280	1.000	.911	.581		Bartlett's Test of Sphericity	Approx. Chi-Square	435865.138
Temp 1	18.580	1.2413	17280	1.000	.670	.224				
Temp 2	18.670	1.2114	17280	1.000	.664	.248				
Temp 3	20.744	.1691	17280	1.000	.803	.587				
Temp 4	21.288	.1193	17280	1.000	.445	.600			df	105
Temp 5	20.101	.1427	17280	1.000	.777	.598			Sig.	.000

In the test of data obtained between gas and wind, the results indicated strong evidence of meeting both reliability and validity standards of exploratory research are listed in Table 3. Cronbach's Alpha was 0.893 and was considered to have very good reliability (above 0.8). In the test of the validity, the ratio of the number of cases to variables was 1329:1 (greater than 5:1), Kaiser-Meyer-Olkin (KMO) was 0.851 and considered to have a very good measure (great than 0.8), Bartlett's test of sphericity was 0.000 ($p<0.001$), the average communality was 0.788 (greater than 0.6). No two-item values are correlated above 0.75 (satisfied with discriminant validity).

In the test of gas and dust, the results met both reliability and validity standards of exploratory research are listed in Table 4. Cronbach's Alpha was 0.954 and is considered to have excellent reliability (above 0.95). In the test of the validity, the ratio of the number of cases to

variables was 1571:1, Kaiser-Meyer-Olkin (KMO) was 0.884, Bartlett's test of sphericity was 0.000 ($p<0.001$), the average communality was 0.845 (greater than 0.6). No two-item values are correlated above 0.75 (satisfied with discriminant validity).

Table 3
Reliability and Validity Analysis of Gas and Wind

Descriptive Statistics				Communalities		Cronbach's Alpha if Item Deleted	Cronbach's Alpha	KMO and Bartlett's Test		
	Mean	Std. Deviation	Analysis N	Initial	Extraction					
Gas 1	.0732	.02044	17280	1.000	.848	-.026[a]	.893	Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.851
Gas 2	.0988	.02883	17280	1.000	.872	-.028[a]				
Gas 3	.1143	.03061	17280	1.000	.837	-.026[a]				
Gas 4	.1304	.03163	17280	1.000	.894	-.032[a]				
Gas 5	.0320	.01024	17280	1.000	.778	-.024[a]				
Gas 6	.2455	.04197	17280	1.000	.922	-.020[a]				
Gas 7	.2718	.04402	17280	1.000	.951	-.019[a]				
Gas 8	.3352	.04457	17280	1.000	.943	-.012[a]		Bartlett's Test of Sphericity	Approx. Chi-Square	348552.915
Gas 9	.3257	.04657	17280	1.000	.944	-.018[a]				
Gas 10	.2521	.03325	17280	1.000	.934	-.020[a]				
Wind 1	.6746	.41432	17280	1.000	.807	-.032[a]				
Wind 2	1.5605	1.86334	17280	1.000	.499	.315			df	78
Wind 3	1.0377	.03534	17280	1.000	.021	-.023[a]			Sig.	.000

[a]. The value is negative due to a negative average covariance among items.

Table 4
Reliability and Validity Analysis of Gas and Dust

Descriptive Statistics				Communalities		Cronbach's Alpha if Item Deleted	Cronbach's Alpha	KMO and Bartlett's Test		
	Mean	Std. Deviation	Analysis N	Initial	Extraction					
Gas 1	.0732	.02044	17280	1.000	.904	.324	.954	Kaiser-Meyer-Olkin Measure of Sampling Adequacy.		.884
Gas 2	.0988	.02883	17280	1.000	.875	.312				
Gas 3	.1143	.03061	17280	1.000	.834	.311				
Gas 4	.1304	.03163	17280	1.000	.794	.312				
Gas 5	.0320	.01024	17280	1.000	.752	.331				
Gas 6	.2455	.04197	17280	1.000	.914	.296		Bartlett's Test of Sphericity	Approx. Chi-Square	341883.743
Gas 7	.2718	.04402	17280	1.000	.955	.292				
Gas 8	.3352	.04457	17280	1.000	.914	.296				
Gas 9	.3257	.04657	17280	1.000	.960	.290				
Gas 10	.2521	.03325	17280	1.000	.947	.303			df	55
Dust	.68	.933	17280	1.000	.446	.952			Sig.	.000

4.3 Correlation Analysis

Correlation analysis between gas and temperature, gas and wind, and gas and dust were conducted. Correlation analysis indicated that positive or negative relations exist between gas and temperature (see Appendix 2). A negative relationship exists between gas and wind (see Appendix 3). Positive relations exist between gas and dust (see Appendix 4).

Table 5 indicates significant correlations between Gas 1, Gas 2, Temp 1, Temp 2 as fair (between 0.3 and 0.49) or good (between 0.5 and 0.69). The degrees of correlation are indicated as fair or good between gas and dust except for Gas 5 and Dust (no correlation). The degrees of correlation are shown as negative fair (-) between Gas 2 and Temp 4, Gas 2 and Temp 5, Gas 5 and Temp 5, and Gas 8 and Wind 2, Correlations values of the degrees of correlation between other items below 0.3 were eliminated.

5. Research Findings And Results

5.1 Research Findings and A Triple-Correlation Theoretical Framework

The correlation analysis results indicate 33 elations exit between data obtained from gas, temperature, wind, and dust. There are 23 relations between gas and temperature, including 20 positive relations and three negative relations. One negative relationship exists between gas and wind. There are nine positive relations between gas and dust. Thus, a Triple-Correlation Theoretical Framework was explored that alleges the triple-correlations between gas and temperature, gas and wind, and gas and dust (Fig.4).

Table 5
Degree of Correlation Between Gas and Temperature, Wind, and Dust

	Temp 1	Temp 2	Temp 3	Temp 4	Temp 5	Wind 1	Wind 2	Wind 3	Dust
Gas 1	fair(+)	fair(+)							fair (+)
Gas 2	good(+)	good(+)		fair (-)	fair(-)				fair (+)
Gas 3	good(+)	good(+)							fair (+)
Gas 4	good(+)	good(+)							fair (+)
Gas 5	good(+)	good(+)			fair(-)				
Gas 6	good(+)	good(+)							good (+)
Gas 7	good(+)	good(+)							good (+)
Gas 8	good(+)	good(+)					fair (-)		good (+)
Gas 9	good(+)	good(+)							good (+)
Gas 10	good(+)	good(+)							good (+)
(+): positive relation; (-): negative relation.									

Based on the existing the ZhongXing Gas Monitoring System (Fig.1) and the research result - a Triple-Correlation Theoretical Framework (Fig.5), a Unified Modeling Language (UML) model was finally developed for demonstrating ZhongXing Innovative Gas Warning system comprising of three layers: the view layer, domain layer, and data access layer (Fig.5). The view layer represents a gas warning system, including the alarming sub-system, warning sub-system, and monitoring sub-system. The data access layer represents databases containing ten gas sensors, five temperature sensors, three wind sensors, and one dust sensor. The domain layer (is also called a business layer, or business logic layer) represents data processing of data obtained from gas databases, temperature databases, and dust database, and correlation analysis of between gas and temperature, gas and wind, and gas and dust.

The business rules of the ZhongXing gas warning system are constrained into three steps, including three decision rules in the domain layer for demonstrating the system logic flows, including data obtained, correlation analysis, and decision activities, as:

- First step: This step was conducted between the Data Access Layer and the Domain Layer. The data were obtained from gas databases (ten), temperature databases (five), wind databases (three), and dust database.
- Second step: This step was run within Domain Layer. The correlation analysis was then conducted between gas and temperature, gas and wind, and gas and dust.
- Third step: This step was established between the Domain Layer and the View Layer. The three decision rules were activated. If the results are normal during the correlation analysis, the data would be forwarded to the monitoring system. If the results indicate an anomaly, the warning system will warn the safety-responsive team directly. If the data outputs of gas reach TLVs, the alarm system will immediately alert the safety-responsive team.

6. Conclusions, Limitations, And Further Research

This research aims to develop an innovation gas warning system for increasing production safety in the underground coal mine industry. The existing gas monitoring systems focus on detecting real-time data obtained from gas sensors and do not analyze whether other sensors' outputs affect gas data. There is a lack of gas monitoring systems in the literature to provide alarms or warning by any anomaly data detected from the correlation analysis of gas data and data acquisition from temperature sensors, wind sensors, dust sensors, etc. This research fills this gap to uncover hidden patterns and correlations between gas and temperature, wind, and dust, and incorporate data analytics into analytics portfolios for developing the innovation gas warning system.

The correlation research method was adopted in this research. 328,320 data outputs were obtained from 19 sensors, including ten gas sensors, five temperature sensors, three wind sensors, and one dust sensors. The research found strong relations between gas and

temperature, wind, and dust. A Triple-Correlation Theoretical Framework was explored, including three correlations - data outputs between gas and temperature, gas and wind, and gas and dust. A UML model was developed for demonstrating the ZhongXing innovative gas warning system. As a result of this research, the ZhongXing gas monitoring system has been upgraded to the ZhongXing Innovative Gas Warning System for user acceptance test to increase coal mining safety on 28 Aug 2020.

The main limitation is that although several industry experts have been involved in this research, the result outcomes are mainly focused on the correlational analysis. Although this research does not provide evidence regarding causal mechanisms between gas and temperature, wind, and dust, the results have indicated existing significant relationships. There is a need to conduct further experimental research such as causal study and investigate the cause-and-effect relationships from the coal mining theory. Further research should also be conducted to test whether the Triple-Correlation Theoretical Framework and the ZhongXing Innovative Gas Warning System might be adopted successfully in other coal mining companies.

Declarations

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Competing interests:

None.

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Authors' contributions:

The name list states the Authors’ contributions to this research.

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Figures

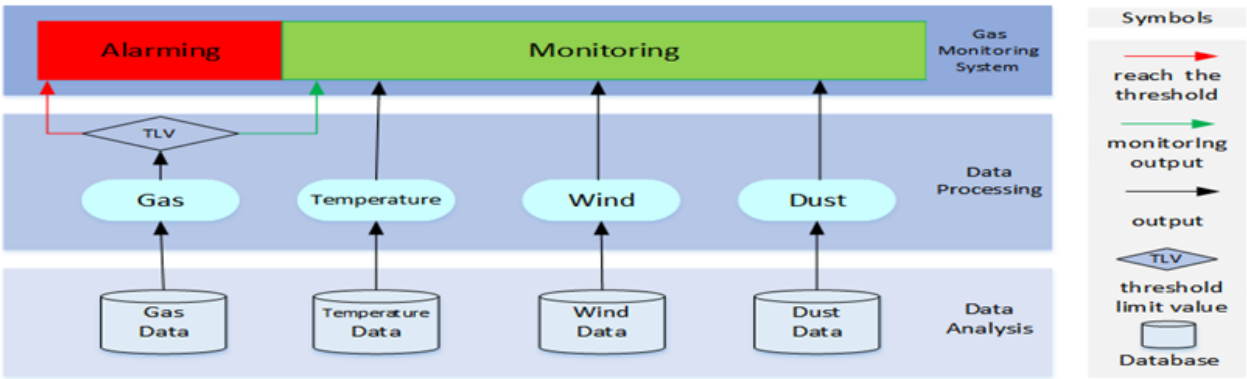

Figure 1

ZhongXing Gas Monitoring System

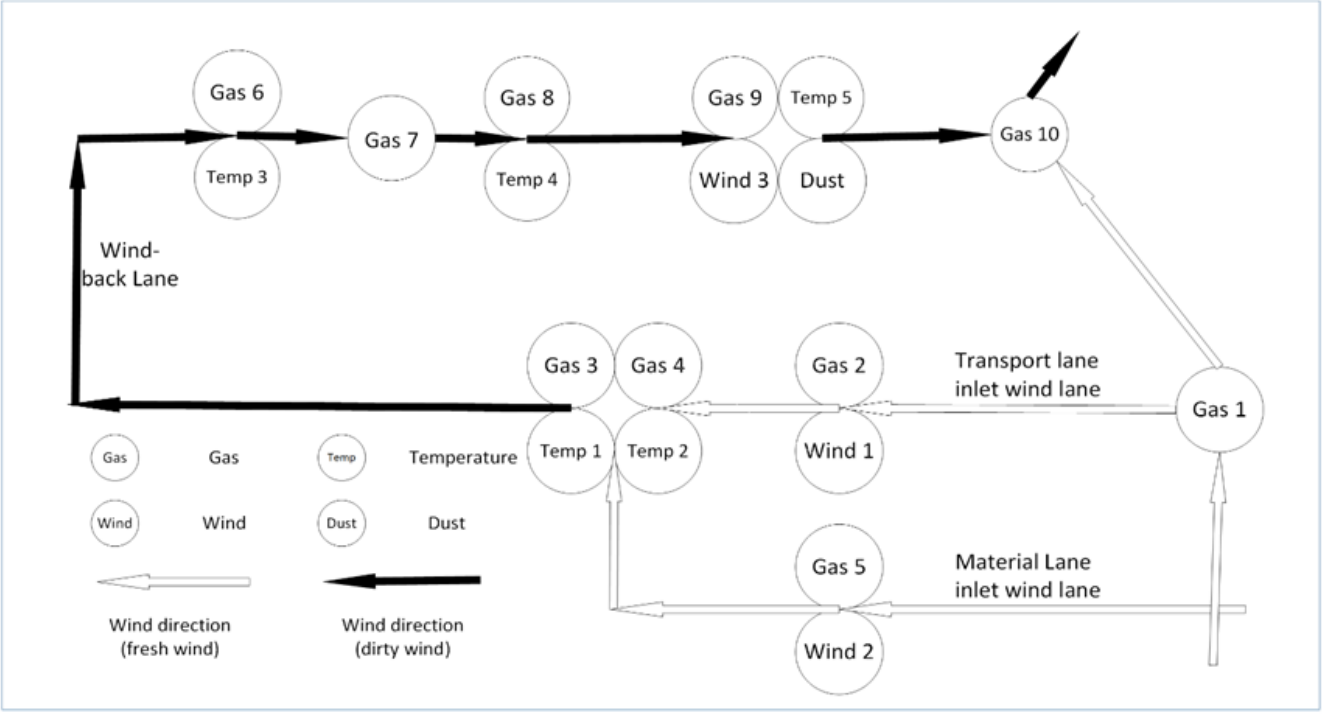

Figure 2

The location of the sensors on Mine no.1209

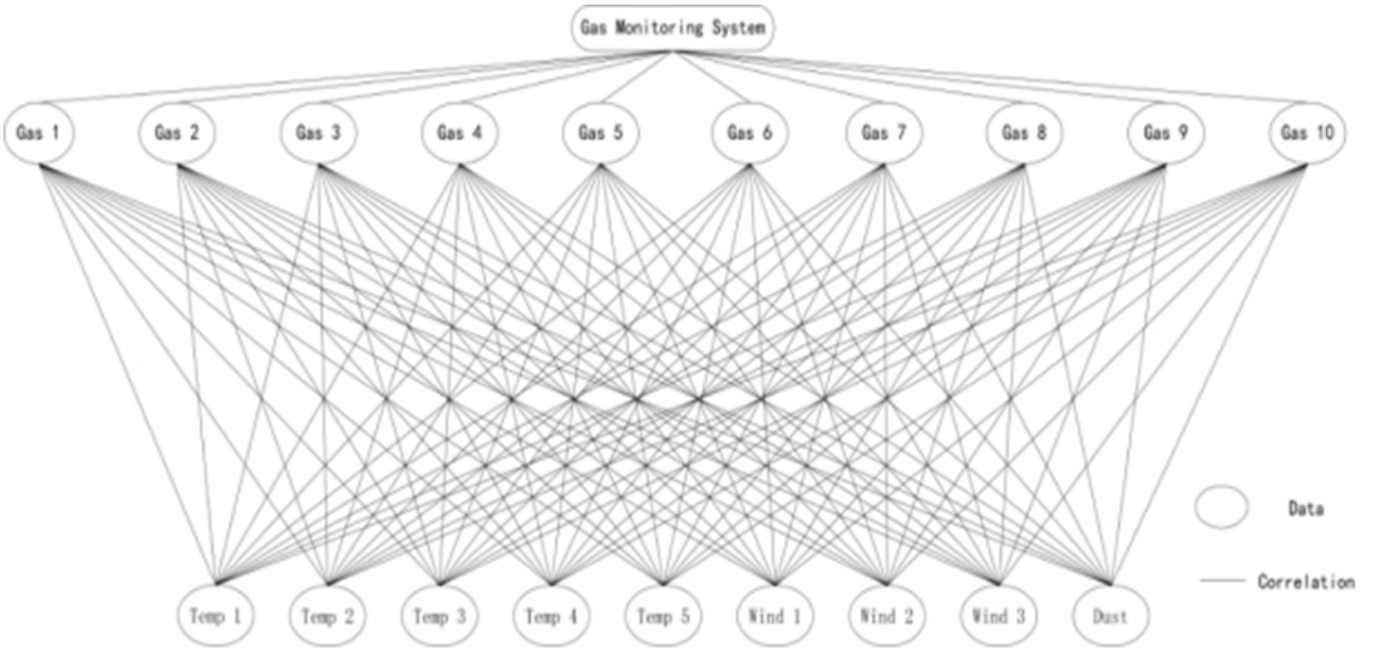

Figure 3

Research Framework

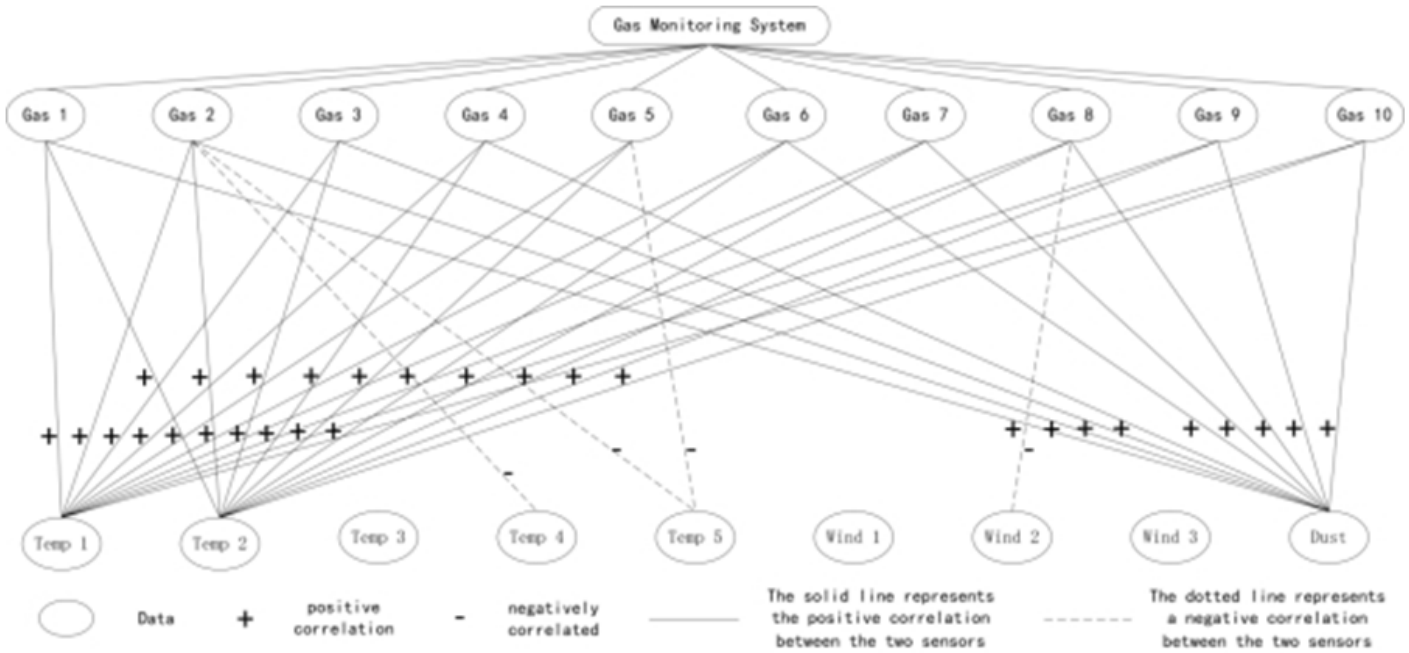

Figure 4

A Triple-Correlation Theoretical Framework

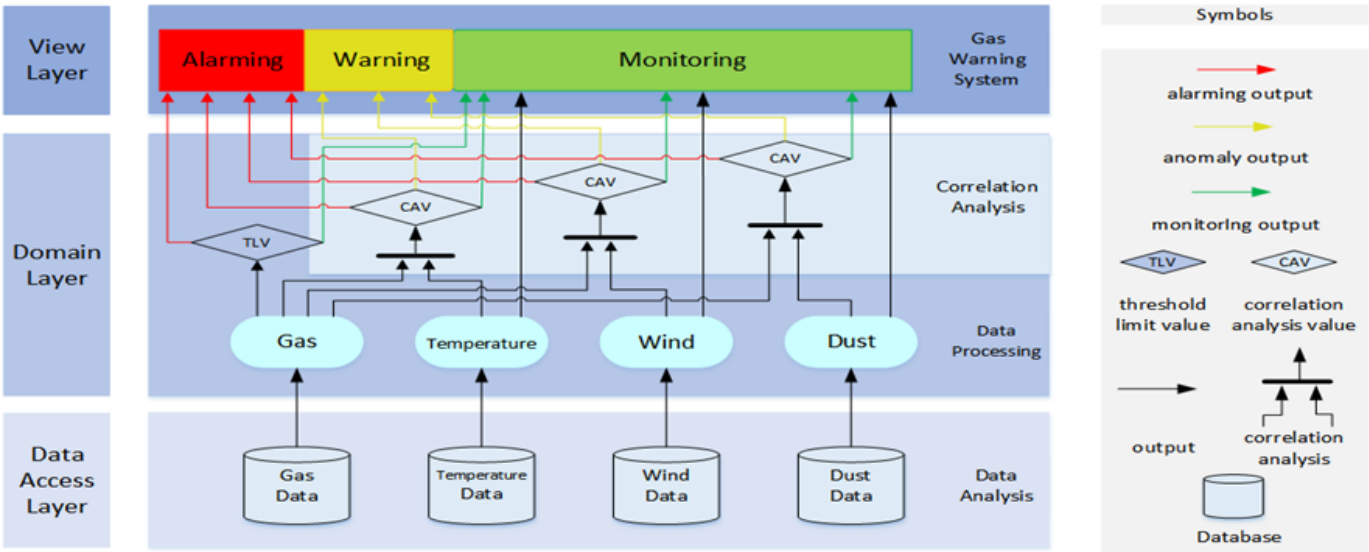

Figure 5

A UML Model of ZhongXing Innovative Gas Warning System

Supplementary Files

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- Appendix.docx