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# Energy-Efficient Boundary Detection of Continuous Objects in Internet of Things Sensing Networks

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**ABSTRACT** Internet of Things (IoT) has been widely used to facilitate environmental perception, where detecting the boundary regions for continuous objects with energy-efficient manner is a challenge to be explored to support domain applications. This paper proposes a novel approach for continuous objects boundary prediction and detection in IoT sensing network, which is called Cloud Model-IoT Sensing Network Collaborative (CM-IoTSNC). Specifically, when an event is potentially occurred, the atmospheric dynamic diffusion model deployed on the cloud is adopted to predict gas diffusion trend in ideal and complex environments, moreover prediction results are transmitted to the IoT devices in the real-time fashion for scheduling security plans in advance. One-hop neighbor nodes are activated by abnormal nodes to determine a more accurate boundary region. Compared our technique with two traditional methods, namely Wireless Sensor Monitoring and Activating One-hop Neighbor Nodes, experimental results show that our method has a good performance in reducing the energy consumption and prolonging the lifetime of the network.

**INDEX TERMS** Boundary detection, continuous objects, IoT sensing networks, energy efficiency, gas dynamic diffusion model.

## I. INTRODUCTION

With the new generation of information technology, Internet of Things (IoT) has developed rapidly and has been applied to support applications in various fields such as environmental protection and military monitoring [1], [2]. IoT nodes connect and communicate with each other through sensing and perception. In addition, they can combine into a large scale of IoT sensing networks [3]. Generally, the collaboration and cooperation of IoT nodes sense the surrounding environment, which can effectively compensate for the shortcomings of current atmospheric environmental monitoring technologies, and achieve real-time monitoring in accident-prone areas, important industrial parks and densely populated areas. Therefore, the monitoring site does not require the participation of a large number of staffs, where IoT devices can transmit sensory data in real time to reduce the workload and avoid some risks. As shown in Fig. 1, the composition of the IoT system can be divided into three levels including information sensing layer, network transport layer and application service layer [4], [5]. Same as sensor nodes in Wireless Sensor Networks (WSNs), IoT nodes are easy to deploy, and can quickly build a self-organizing network that is not easily restricted by the surrounding environment. Most nodes in the network are battery-powered, which are difficult to be recharged due to the harsh environment [6], [7]. Therefore, extending network lifetime and reducing energy consumption are key issues in IoT sensing networks. Note that data communication between sensor nodes requires more energy than sensing and data processing [8]. Thus, cloud architecture is

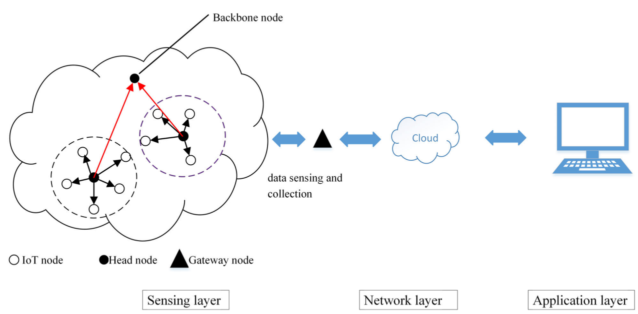


**FIGURE 1.** Internet of Things (IoT) architecture.

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adopted to reduce data communication between nodes, which can greatly reduce the energy consumption in the network. In recent years, cloud computing has become an indispensable part of processing IoT data [9]. The cloud has powerful data analysis capabilities and with less restrictions in terms of memory and energy. The integration of cloud computing and IoT sensing network can effectively solve the problems of high energy consumption, limited storage capacity and limited computing resources [10].

With the development of mobile technology and wireless communication, IoT and cloud computing have become the most important network paradigm [11]. In this paper, combined with cloud computing, IoT sensing networks are used to track and predict toxic gas diffusion. The leakage and spread of toxic gases are complex continuous processes that can bring about serious air pollution and casualties. The most critical issue for this type of problem is to determine the contaminated areas immediately and accurately. However, tracking and locating continuous objects in practice are very difficult, requiring a large number of message exchanges and cooperations between sensor nodes to estimate the motion and position information of the objects [12]. The most traditional approach for continuous object tracking is to transit all the monitoring information to the backbone node [13], which depletes the energy quickly for the huge amount of report messages and the large number of communications between IoT nodes, resulting in a shortened network lifetime. In [14], the authors propose the concept of sleeping nodes and use the activation mechanism to activate one-hop neighbor nodes of abnormal nodes. The accurate boundary can be determined by the data information of abnormal nodes and neighbor nodes. This method always sends activation signal repeatedly and generates unnecessary energy consumption. Some researchers propose the idea of adding mobile sensor nodes to static sensor networks in order to quickly detect and resolve perceptual holes in the network and improve the accuracy of boundary information [15]. The disadvantage of this method is to increase the economic investment due to the highest price of mobile nodes. In addition, mobile nodes are not suitable for some special environments, such as mountains and rugged places. Proposed techniques can produce better results under certain conditions, but reducing energy consumption need to be considered.

In view of the above problems, we propose a novel method of Cloud Model-IoT Sensing Network Collaborative (CM-IoTSNC) in this paper. The main goal is to realise the cloud prediction with gas diffusion model and to transmit regional boundary with IoT nodes to generate regional position and advanced safety path plans. The main research direction of this paper is the tracking of continuous objects, that is, the location of the toxic gas pollution boundary area. The main contents of this paper are listed as follows:

- Combined with ideal and complex meteorological conditions, a dynamic diffusion model is proposed to simulate the gas diffusion.
- We propose the method of CM-IoTSNC for tracking dangerous areas of toxic gas leakage. The scheme utilizes the communication between cloud and IoT nodes to locate the hazardous boundary region.
- The processes of tracing continuous objects boundary by three methods are simulated and visualized in the form of simulation graph and we compare the energy consumption about these three methods.

In this paper, two parameters are selected, including the number of nodes in the network and the skewness of nodes distribution. A large number of experiments are conducted to explore the impact of different parameters on the proposed methods. The experimental results demonstrate the effectiveness and efficiency of our method, and the comparative experiments show that our technology has better performance.

The rest of this article is organized as follows. Section II introduces the definition of network nodes, the energy model and gas diffusion model. Section III presents the principle of three methods. Section IV shows the simulation results of atmospheric diffusion model and three methods, then make a comparison of energy consumption. Section V reviews and discusses related work. Finally Section VI concludes this work.

## II. PRELIMINARIES

This section mainly introduces network nodes definition, atmospheric dynamic diffusion model and energy model, all of which are used in the following sections.

### A. NETWORK NODES DEFINITION

*Definition 1:* Network Node. A network node is represented as a tuple (*id*, *loc*, *sen*) where:

- *id* is the unique identifier.
- *loc* is the geographical location of node.
- *sen* indicates sensory data.

The *loc* of a Network Node is represented by its longitude and latitude. It is the main information to determine the geographic location of sensor nodes. *sen* is the value of monitored variable monitored by the sensor nodes, which reflect the normal or abnormal state of the nodes.

The monitor area is indicated by two elements: (*length*, *width*), which represent the length and width of the area. We divide the whole region evenly into square grid cells, that the side length of each grid cell is $\sqrt{2}r$. Where $r$ represents the communication radius of the sensors [16].

### B. ENERGY MODEL

The main consideration in IoT sensing network is to extend the lifetime of the network and minimize the energy consumption of the nodes. Therefore, we use the energy model commonly adopted in the field of IoT to calculate the energy consumption during the entire monitoring process [17]. The parameters of the energy model are presented at Table 1.

Where $E_{elec}$ is the energy consumption of the transmission and receiver electronics for per bit and $\epsilon_{amp}$ is the transmitting

**TABLE 1.** Parameters in the energy model.

| Name | Description |
|---|---|
| $E_{elec}$ | Energy consumption constant of the transmit and receiver electronics |
| $\epsilon_{amp}$ | Energy consumption constant of the transmit amplifier |
| $k$ | The number of bits in one pocket |
| $d$ | The distance of transmission |
| $n$ | The attenuation index of transmission |
| $r$ | The communication radius of sensor n-odes |
| $E_{Tx}(k,d)$ | The energy consumed to transmit a $k$ bit packet to a distance $d$ |
| $E_{Rx}(k)$ | The energy consumed to receive a $k$ bit packet |

and amplifying parameter. $E_{Tx}(k,d)$ represents the energy consumed for transmitting a packet of $k$ bits within a distance $d$, while $E_{Rx}(k)$ represents the energy consumption when receiving a packet of $k$ bits, the formulae are given as follows:

$$E_{Tx}(k,d) = E_{elec} \times k + \epsilon_{amp} \times k \times d^n \tag{1}$$

$$E_{Rx}(k) = E_{elec} \times k \tag{2}$$

While $k$ bits packet are passed from node $i$ to neighboring node $j$, its energy consumption is as follows:

$$E_{ij}(k) = E_{Tx}(k,d) + E_{Rx}(k) \tag{3}$$

The energy consumption from one node to another node or backbone node are different, since the backbone node does not take the energy limit into account when receiving and transmitting data. Consequently, $E_{ij}(k)$ is as follows:

$$E_{ij}(k)=\begin{cases} E_{elec} \times k + \epsilon_{amp} \times k \times d^n & \text{if } j \text{ is backbone node} \\ 2 \times E_{elec} \times k + \epsilon_{amp} \times k \times d^n & \text{otherwise} \end{cases} \tag{4}$$

The energy required to transmit a message form sensor node $i$ to node $j$ is same as that required to transmit a message from sensor node $j$ to node $i$, in another word, $E_{ij}(k) = E_{ji}(k)$.

In the Table 1, the value of the propagation attenuation index $n$ can be determined by the surrounding environment. When the sensor node transmits information without obstacle, the value of $n$ takes 2. Otherwise, when it is transmitted in a building with dense vegetation, the value of $n$ takes 3 to 5.

### C. GAS DYNAMIC DIFFUSION MODEL

Gaussian model is often used to study gas diffusion law and concentration distribution because of the small amount of calculation and the wide range of applications [18]. The Gaussian model is divided into Gaussian plume model and Gaussian puff model. The former applies to the continuous diffusion of gases, the latter applies to the instantaneous diffusion of gases [19], [20]. There is no need to set leakage diffusion time $t$ in the Gaussian plume model, and the calculation result is the concentration distribution of toxic and harmful gases in the steady state. So the gas concentration value at any time cannot be calculated. However, the Gaussian puff model has the setting of time $t$, which can simulate the concentration distribution of gas diffusion at any time [21], [22]. Therefore, in this paper, a dynamic diffusion model is established by using Gaussian puff model and combining with the theoretical basis of superposition model. This model simulates the release of continuous plume through a series of sequential release of puff clusters. The basic principle can be described as: the continuous leakage process is regarded as the superposition of a limited number of instantaneously processes. Thus, the concentration of a certain point in the space at any time is the result of the superposition of multiple puff groups at this point [23], [24]. The specific formula of the dynamic diffusion model is shown as follows:

$$C(x,y,z) = \int_0^t C_i'(x,y,z,t)dt \approx \sum_i^n C_i'(x,y,z,t)\Delta t \tag{5}$$

$$\begin{aligned} C_i'(x,y,z,t) &= \frac{Q}{(2\pi)^{\frac{3}{2}}\sigma_x\sigma_y\sigma_z}\exp\left[-\frac{(x-x_0)^2}{2\sigma_x^2}\right]\exp\left[-\frac{(y-y_0)^2}{2\sigma_y^2}\right] \\ &\quad \times\left\{\exp\left[-\frac{(z-H_r)^2}{2\sigma_z^2}\right]+\exp\left[-\frac{(z+H_r)^2}{2\sigma_z^2}\right]\right\} \\ &= \frac{Q}{(2\pi)^{\frac{3}{2}}\sigma_x\sigma_y\sigma_z}\exp\left[-\frac{(x-ut)^2}{2\sigma_x^2}\right]\exp\left[-\frac{y^2}{2\sigma_y^2}\right] \\ &\quad \times\left\{\exp\left[-\frac{(z-H_r)^2}{2\sigma_z^2}\right]+\exp\left[-\frac{(z+H_r)^2}{2\sigma_z^2}\right]\right\} \end{aligned} \tag{6}$$

where $C(x,y,z)$ is the concentration of the $(x,y,z)$ point at time $t$; $C_i'(x,y,z,t)$ is the concentration produced by each instantaneous process. $Q$ represents the leakage rate during the diffusion processes; $u$ is the composite diffusion rate; $t$ represents the diffusion time of the leakage; $H_r$ represents the effective height of the leakage source; $\sigma_x$, $\sigma_y$, $\sigma_z$ are represent the diffusion parameters of puff in X axis and Y axis and Z axis, $\sigma_x = \sigma_y = ax^b$, $\sigma_z = cx^d$, which can be obtained by querying the Pasquill-Gifford model [25].

Improve the parameters in the model to make the simulation results more close to the actual situation [26]. The following is a detailed introduction.

- composite diffusion rate. Toxic gas diffusion is affected by many factors, the most direct factor is the state of the airflow. The composite velocity is proposed to express the velocity accurately.

$$u = av + s$$

where $s$ indicates the diffusion speed of the gas itself, $a$ is the wind speed coefficient. Taking wind speed $v$ and gas diffusion velocity $s$ into consideration, the composite diffusion velocity ($u$) of observation point is obtained by combining the two elements.

- Attenuation coefficient. Due to the natural absorption in the diffusion processes, the poisonous gas concentration will decrease slightly. In order to simulate the actual situation effectively, the attenuation coefficient $g$ is introduced, and its value range is $0.001 \leq g \leq 0.01$. The expression is as follows:

$$C(x,y,z) = \sum_{i=1}^{n}(1-g)^{n-i}C_i'(x,y,z,t)$$
$$C_i^n \triangleq \{C(i), C(i+1), \cdots, C(n)\}, \quad \forall n \geq i > 0$$

where $n$ is the total number of puff clusters, divided by continuous plumes; $i$ represents the sequence number of the current puff in the whole processes. $\{C(i), C(i+1), \cdots, C(n)\}$ represent the concentration of the puff in the corresponding sequence. Superimposing the concentration produced by all instantaneous processes and you can obtain the result of the diffusion of the entire continuous processes.

## III. THEORETICAL ANALYSIS

After the leakage and diffusion of toxic gas, there is an invisible continuous dangerous area of which boundary is difficult to detect and determine. In this paper, three methods are used to find the boundary of dangerous area, and then determine the most energy-saving method. As mentioned in Section III-A, we present the traditional method of Wireless Sensor Monitoring (WSM). The method of Activating One-hop Neighbor Nodes (AONN) is shown in Section III-B. In Section III-C, we propose the novel method of Cloud Model-IoT Sensing Network Collaboration (CM-IoTSNC).

### A. WIRELESS SENSOR MONITORING (WSM)

The nodes in the entire sensing networks are actived, and each node communicates with the backbone node in real time. When a leakage occurs, nodes can quickly detect the abnormal situation, and can quickly locate the dangerous area, then determine the dangerous boundary according to its own situation (abnormal or normal). In Fig. 2, the shaded area

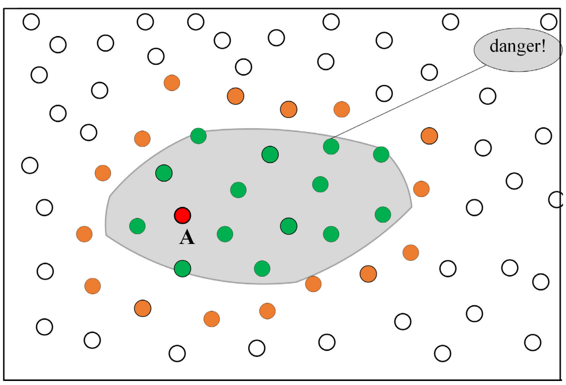



**FIGURE 2.** **Hazardous areas detected by the method of WSM.**

represents the abnormal region, the white circles represent the normal actived nodes, the green circles refer to abnormal nodes, and the orange circles represent the boundary nodes. Where, the boundary node is defined as a given node whose measured value is lower than the set threshold and there is at least one abnormal node in its one-hop neighbor nodes under the premise of missing node in the sensor network. These boundary nodes contain the whole dangerous area inside to ensure security. This method can identify the dangerous areas in a short time, but the network lifetime is short because the nodes are in the working state for a long period of time and the battery energy consumption is higher.

### B. ACTIVATING ONE-HOP NEIGHBOR NODES (AONN)

The network is divided into grid cells, each with randomly selects a head node. Under normal circumstances, all head nodes in the grid cells are periodically detected, while the rest of nodes are in the sleeping state. The sleep nodes do not detect the concentration, but can receive the data packets form neighbor nodes. This detection mechanism can reduce the energy consumption of the sensing network. Once head node detects an anomaly, it reports the backbone node and activates its one-hop neighbor nodes by sending packets. Algorithm 1 introduces the processes of node activation in detail.

**Algorithm 1** AbnNeiDet

**Require:** $ct$: concentration threshold
$c$: the concentration of node
$r$: the communication radius of sensors
$o$: one node
$no$: one-hop neighbor nodes
$nbo$: one-hop neighbor boundary nodes
**Ensure:** AbnormalNeiList: set of abnormal neighbor nodes
1: **for** each head node **do**
2: periodically detect $c$
3: DetectionNodeList.add(head node)
4: **end for**
5: **for** each node $o$ in DetectionNodeList **do**
6: **if** $c > ct$ **then**
7: AbnormalNodeList.add($o$)
8: activates $o.no$
9: extract $no.nbo$ and DetectionNodeList.addAll($nbo$)
10: $nbo$ continue to detect $c$
11: **else**
12: **if** $o$ and its all active $no$ with normal concentration **then**
13: $o$ is sleep and DetectionNodeList.delete($o$)
14: **end if**
15: **end if**
16: **end for**
17: send abnormal information in AbnormalNeiList to backbone node
18: **return** abnormal neighbor nodes information

We let head nodes periodically detect concentration and place them into *detection node list* (denote Detection NodeList) (lines 1-4). When no abnormal conditions occur, the rest of nodes are in the sleeping state in order to save battery power. For each node in DetectionNodeList (line 5), if the current concentration value is detected to be greater than the threshold value (line 6), the node will be added to the *abnormal node list* (denote AbnormalNodeList) (line 7). Meanwhile, data packets are sent to activate its one-hop neighbor nodes (line 8). For example, all nodes within communication radius of node are considered as one-hop neighbor nodes and put into *one-hop neighbor list*. If the node broadcasts a control packet to its all neighbor nodes in list, these neighbors will be activated and continue to detect their own concentration. Here, in order to reduce energy consumption, we propose to extract the boundary nodes of all activated neighbor nodes and place them into DetectionNodeList (line 9). Specifically, select a certain step size in advance, which is the constant value to divide all abnormal nodes into several parts. Then arrange all the neighbor nodes in ascending order (or descending order) according to the x-coordinate. After sorting, we extract two nodes with maximal x-coordinate and minimal x-coordinate and place them into DetectionNodeList. For y-coordinate, we use the same way to sort the two nodes with maximal y-coordinate and minimal y-coordinate. The extracted nodes serve as boundary nodes. Boundary nodes are selected to reduce the redundancy of coverage and the number of activation packets sent when activating neighbor nodes. If every abnormal node activates its one-hop neighbor nodes, it will cause repeated activation of a large number of nodes, resulting in waste of battery energy. Continue to detecting the concentration (line 10) and then back to line 6 to recycle this processes. If one node detects itself without errors and its all neighbor nodes are also normal (line 12), this node will be deleted from DetectionNodeList and will turn into the sleeping state (line 13). In the whole processes, not all sensor nodes send abnormal data to backbone node. In order to reduce the energy consumption and blockage of the transmission channel caused by a large amount of data uploading, the general data transmission method is that the neighbor nodes in the communication radius upload the data to the head node, and then the head nodes upload to the backbone node (line 17). Finally, we can obtain the information of abnormal neighbor nodes.

The processes of activating neighbor nodes are shown in the Fig. 3. The head node *A* detects itself is abnormal then activates all one-hop neighbor nodes within the communication radius, that is, the yellow circles (the dotted circle is the communication range of the node, the direction of Node *A* actives Node *B* is denoted by a arrow form A to B). If the neighbor node is abnormal, it needs to activate its one-hop neighbor nodes again. For example, assuming all yellow nodes detect an anomaly, then they need to activate their one-hop neighbor nodes. The blue arrow indicates the activation processes, and the blue nodes represent all the one-hop neighbor nodes of yellow nodes. Where, the purple arrow represents the path of data uploaded from node *A* to backbone node, which is the shortest path.

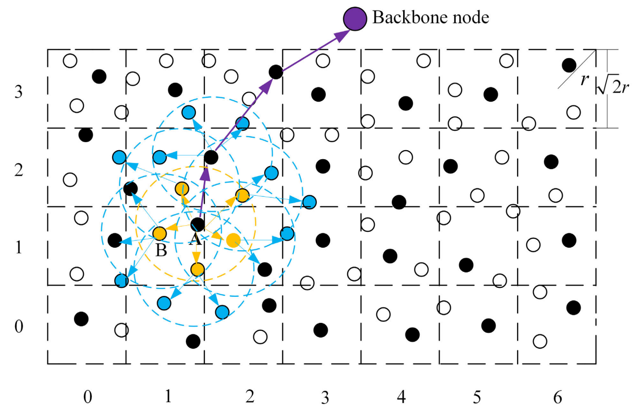



**FIGURE 3.** Process diagram of abnormal head node activate its one-hop neighbor nodes.

This method can determine the boundary of dangerous area by continuously activating one-hop neighbor nodes of abnormal nodes. This approach saves a lot of energy compared to the method of WSM. Because the sleeping node is introduced, which does not consume energy under normal conditions. However, in the event of an abnormal situation, this method needs to activate a large number of neighbor nodes in order to determine the dangerous area more accurately. The more neighbor nodes are activated, the greater the energy consumption will be. How to reduce this part of energy consumption is the main problem of study. Therefore, we propose the method of Cloud Model-IoT Sensing Network Collaboration (CM-IoTSNC) in this paper, which reduce energy consumption by activating a small number of neighbor nodes.

### C. CLOUD MODEL-IoT SENSING NETWORK COLLABORATION (CM-IoTSNC)

Combine cloud which has large computing power with IoT sensing network to monitor and predict gas diffusion. According to the dynamic diffusion model of toxic gas introduced in Section II-C of this paper, the simulation of gas diffusion can be achieved by the combination of real-time meteorological conditions. The schematic diagram of CM-IoTSNC method is shown in Fig. 4. The process is consisted of the following four steps:

- *Step 1*: The head nodes are used to detect whether the condition is normal or not periodically in the network. If an abnormal condition is detected, the head node will report its data immediately to the backbone node and activates its one-hop neighbor nodes for detection. For example, when the head node (such as node *A*) detects an abnormal condition, it uploads data to the backbone node (the purple arrow indicates the upload path). Then the backbone node sends packets to activate abnormal node's one-hop neighbor nodes (such as the green circles). Moreover, according to the state of the head node and the activated one-hop neighbor nodes, the accurate leakage source can be determined. Generally, only

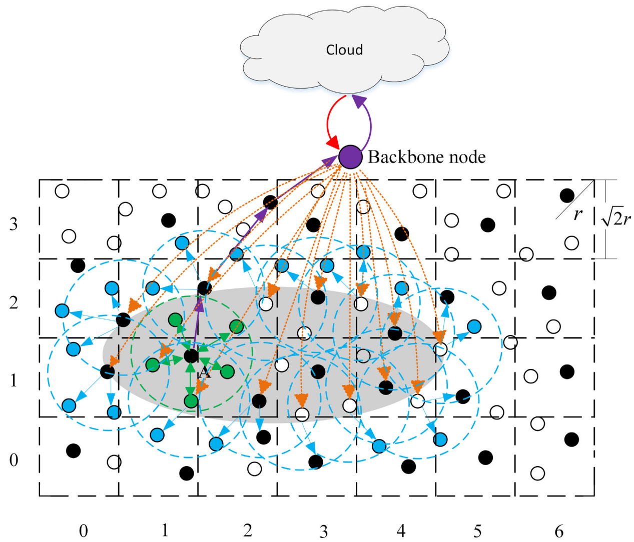



**FIGURE 4.** Schematic diagram of collaboration between cloud and IoT sensing networks.

one-hop neighbor nodes of the head node need to be activated to determine the exact location of the leakage source. Because each grid cell corresponds to a head node, if the leakage source is in another grid, it will be detected by the corresponding head node.

- *Step 2*: The backbone node uploads abnormal data to the cloud for prediction of toxic gas diffusion. Specifically, the exact location of leakage source can be determined by *Step 1*. Thus, the backbone node sends the accurate location of leakage source and weather information to cloud, and then the cloud starts to simulate the atmospheric diffusion based on the pre-determined gas dynamic diffusion model.
- *Step 3*: The prediction results of the cloud are transmitted to the network and the corresponding boundary nodes are activated to detect the dangerous area. Definitely, cloud transmits the boundary nodes information to the backbone node, and then the backbone node sends packets to activate the boundary nodes (such as the red arrow indicates that the information is transmitted from the cloud to the backbone node, the orange arrow means that the information is transmitted from the backbone node to the IoT nodes).
- *Step 4*: Correct and adjust the boundary of the dangerous area by activating one-hop neighbor nodes of the activated boundary nodes. The boundary nodes that identified in *Step 3* activate their one-hop neighbor nodes (such as the blue circles) in the network. In this way, the boundary region can be corrected quickly to avoid inaccurate detection results caused by the difference between the model prediction results and the actual contaminated areas.

This method reduces the number of nodes that need to be activated and the communication times between nodes, which greatly reduces the energy consumption and prolongs the lifetime of the network.

In addition, in severe weather conditions, such as windy weather, the gas spreads quickly and can cause widespread pollution in a short time. However, the sensing network only covers a specific monitoring area, which cannot monitor the area outside the monitoring range. When the diffusion range exceeds the monitoring range of the sensor nodes, the parameters of the atmosphere cannot be detected, and the severity of the pollution cannot be measured. The method of CM-IoTSNC can predict the hazardous area and then activate sensor nodes for detection in advance. The method can also predict whether the unmonitored area is invaded by toxic gases and predict its concentration distribution. This will help the emergency management department to quickly grasp the spatial impact of toxic gases, plan routes in advance, make various rescue decisions, and minimize the loss of personnel and property caused by accidents.

## IV. IMPLEMENTATION AND EVALUATION

The prototype has been implemented in Java program and Matlab 9.0 (R2016a), and experiments have been conducted on a desktop with Intel(R) Core(TM) i5-3470 CPU @ 3.20GHz, 8GB of memory and a 64-bit Windows 7 system. The experiment settings and evaluation results are presented in the following.

### A. EXPERIMENT SETTINGS

#### 1) GAS DYNAMIC DIFFUSION MODEL PARAMETER SETTINGS

This part simulates the gas diffusion in ideal environment and complex environment. In the ideal environment, we assume that there is no interference from the outside, and the gas only depends on its own diffusion rate for diffusion. Under complex meteorological conditions, that is, changing the wind direction and wind speed simultaneously. The meteorological changes considered by simulation are shown in the Table 2. The initial gas thickness is $650kg/km^2$, the wind speed increased from $3m/s$ to $5m/s$, and the wind direction increased from 5° to 20°, in which the clockwise direction of the coordinate system X-axis is the positive direction.

**TABLE 2.** Complex meteorological conditions.

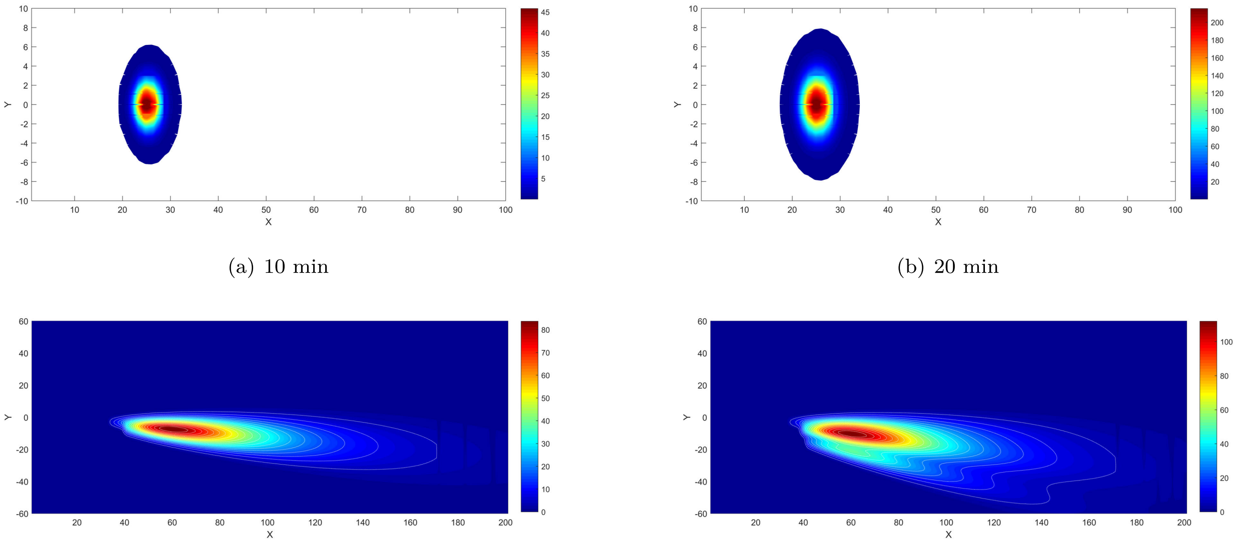
| Wind speed | Wind direction | Wind speed coefficient |
|---|---|---|
| 3 | 5 | 0.944 |
| 4 | 10 | 0.888 |
| 4 | 12 | 0.866 |
| 5 | 20 | 0.777 |

#### 2) PARAMETER SETTINGS IN THE NETWORK

The parameter settings for our experiments are presented in Table 3. The region size is set to $300m \times 300m$. The concentration threshold is set to $70mg/(m^2)$. When the measured value is larger than the threshold, it will be regarded as abnormal situation. The node communication radius is set to $30m$. Generally, the variable $E_{elec}$ is set to 50nJ/bit and $\epsilon_{amp}$ is set to $0.1nJ/(bit \times m^2)$. In the experiments, we choose different number of sensor nodes (the number of sensor nodes

**TABLE 3.** Parameters settings in the experiments.

| Parameters Name | Value |
|---|---|
| Area size | $300m \times 300m$ |
| Number of sensor nodes | 1,500 to 2,500 |
| Skewness degree | 10% to 30% |
| Communication radius | 30m |
| Number of bits in one packet($k$) | 1 |
| Attenuation index of transmission($n$) | 2 |
| Energy consumption constant for the transmit and receiver electronics ($E_{elec}$) | 50nJ/bit |
| Energy consumption constant for the transmit amplifier ($\epsilon_{amp}$) | $0.1nJ/(bit \times m^2)$ |
| The threshold of concentration | $70mg/(m^2)$ |
| Time interval for head node detection | 10 seconds |



(a) 10 min

(b) 20 min

(c) 10 min

(d) 20 min

**FIGURE 5.** (a) and (b) are gas diffusion in ideal environment, (c) and (d) are gas diffusion in complex environment.

denote $N$): $N$ = 1500, 2000, 2500. Then sensor nodes are distributed in the network according to different skewness degrees (skewness degree denote $sd$): $sd$ = 10%, 20%, 30%. Generally, the skewness degree indicates the unevenness of distribution of smart devices in the whole. The calculation formula is: $sd = (dn - sd) \div N$, where $dn$ represents the number of smart things in dense subregions, $sn$ is the number of smart things in sparse subregions, and $N$ is the sum of $dn$ and $sn$ [27].

### B. EVALUATION RESULTS

In this section, we introduce three parts including simulation results of the atmospheric dynamic diffusion model; Energy consumption of three methods under different node numbers and different skewness distributions; The visualization of three methods to find the boundary of continuous objects are realized by simulation. In the following, we will explain them in detail.

#### 1) GAS DYNAMIC DIFFUSION MODEL SIMULATION RESULTS

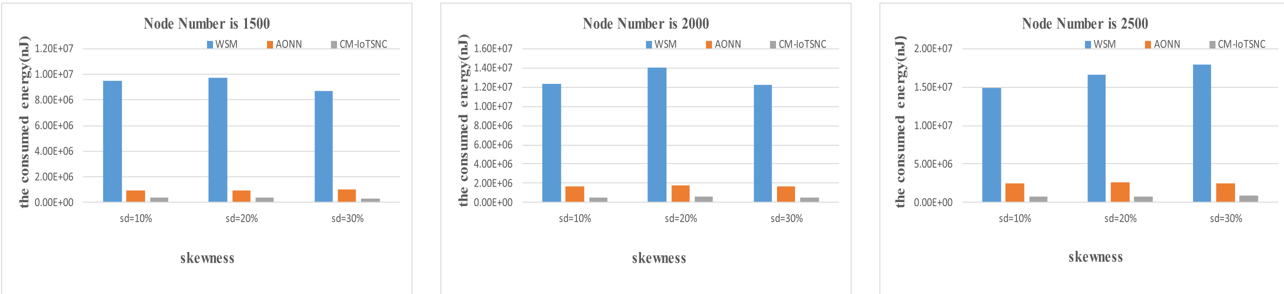
In the ideal environment, the diffusion trend rule and the simulation diagram are shown in Fig. 5(a) and Fig. 5(b). In the absence of wind, radioactive gas depends on its own diffusion rate to spread around, and the gas concentration increases with time. Since there is no influence of wind speed, the overall diffusion is gradually spread out from the leak source. By comparing Fig. 5(a) and Fig. 5(b), it can be seen that, within the interval of 10 min, the newly increased risk area is small and regular, but the concentration value increases greatly.

In the complex environment, the diffusion processes of radioactive gas are shown in Fig. 5(c) and Fig. 5(d). In the same time interval, compare Fig. 5(c) and Fig. 5(d), when affected by meteorological conditions, the diffusion of gas is different from that under ideal conditions. The hazardous area has a large coverage and its shape is irregular, which more closer to the real environment.

Understanding and analyzing the dynamic diffusion model, which achieve dynamic simulation of gas diffusion under ideal geographical conditions and complicated conditions. This theory can be applied to the latter methods.

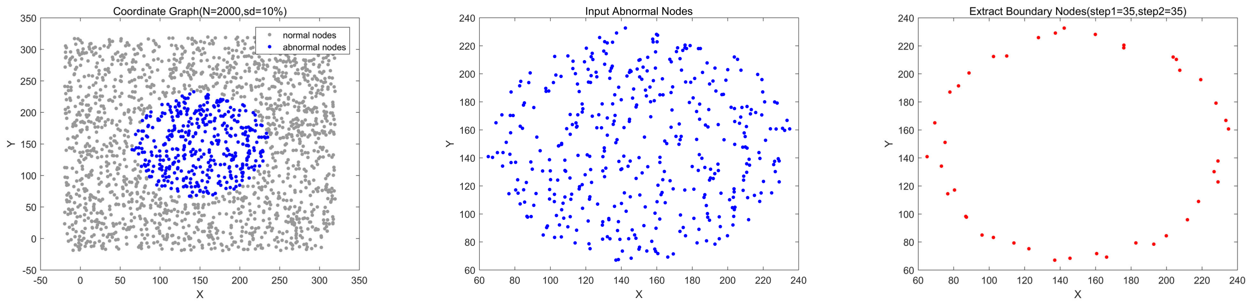
#### 2) ENERGY CALCULATION OF THREE METHODS

In this part, evaluate the performance of the proposed methods with a large amount of experiments. The distribution density of nodes and the skewness degree have an great




(a) (b) (c)

**FIGURE 6. Comparing and analyzing the energy consumption of the three methods.**




(a) normal and abnormal nodes (b) inputting abnormal nodes (c) outputting boundary nodes

**FIGURE 7. The coordinate graphs of dangerous area.**

influence on the results. Therefore, this paper conducts several experiments by changing the following parameters. (i) various numbers of sensor node (ii) different skewness degree. By comparing the three methods, we can clearly know that the CM-IoTSNC method activates the least number of nodes, followed by AONN method and WSM method. However, due to the different distance of data transmission, it is difficult to directly obtain the energy consumption of the three methods. Therefore, the effectiveness of our proposed method is verified by calculating energy consumption.

The number of sensor nodes varies from 1,500 to 2,500, and the nodes distribution skewness degree varies from 10% to 30%. Fig. 6 shows the consumed energy comparison of three methods under different number of sensor nodes and different skewness degree in the form of bar graph. The blue, orange, and gray rectangle respectively represent the energy consumption of three methods under the corresponding number of nodes and skewness degree. According to these figures, we know that the more the number of sensor nodes, the more the consumed energy is required. In the whole process, the method of CM-IoTSNC consumes the least energy and achieves the best results, and the method of WSM consumes the most energy.

### 3) EXPERIMENTAL RESULTS OF THREE METHODS

Taking $N = 2000$ and $sd = 10\%$ as the example. Assume that the location of the leakage source is the center of the monitored area, that is, the position with coordinates (150, 150). As shown in Fig. 7(a), set the dangerous zone to the area where the blue nodes are located, and extract the entire dangerous area as shown in Fig. 7(b). According to Section III of this paper, the boundary nodes of the dangerous area are extracted in step size 35 as shown in Fig. 7(c). The dangerous area is separately searched by three methods, and compare the energy consumption in the processes. The entire processes are described in detail through simulation.

(i) Wireless Sensor Monitoring (WSM)

When monitoring in the traditional way, as shown in Fig. 8, all nodes are actived (such as the blue nodes). When an abnormality is detected, the nodes data are transmitted to the backbone node in real time, and the backbone node can directly determine the dangerous area based on the data information. Normal blue nodes turns into abnormal red nodes, and the red nodes area is the dangerous area.

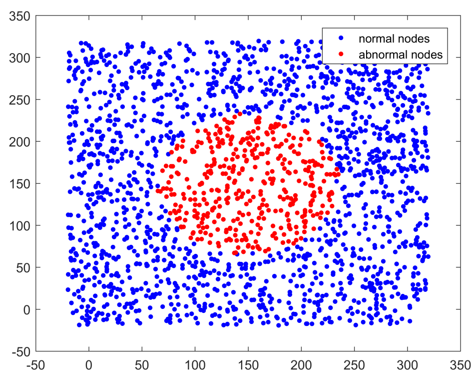
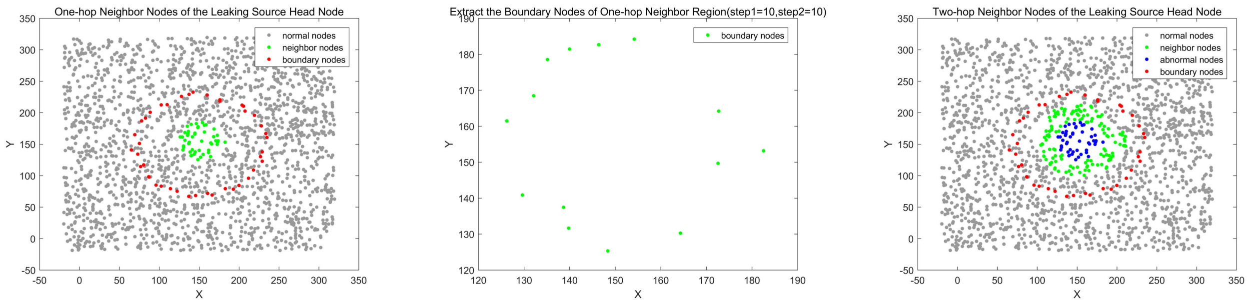
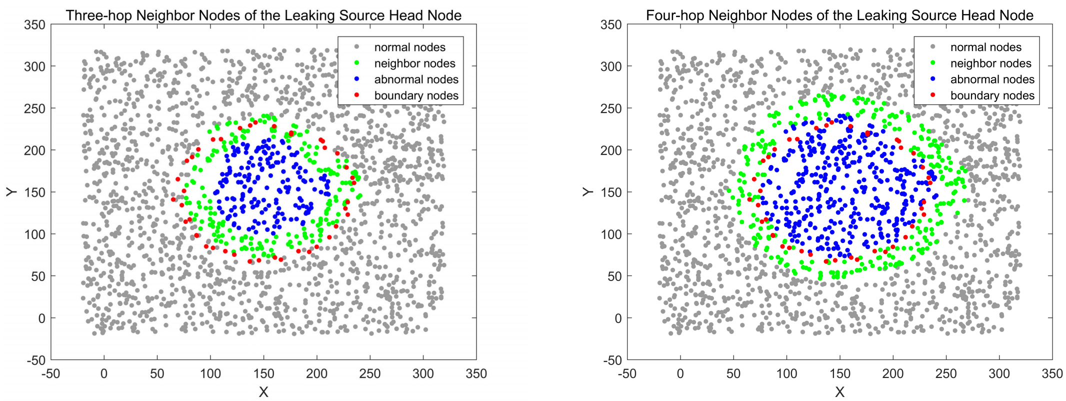



**FIGURE 8. The coordinate graph of the method of WSM.**




(a) one-hop neighbor nodes (b) outputting boundary nodes (c) boundary node's neighbor nodes

**FIGURE 9.** **The process diagram for activating one-hop and two-hop neighbor nodes of leakage source node.**




(a) three-hop neighbor nodes (b) four-hop neighbor nodes

**FIGURE 10.** **The process diagram for activating three-hop and four-hop neighbor nodes of leakage source node.**

(ii) Activating One-hop Neighbor Nodes (AONN)

When a leakage occurs, the head node located in the corresponding grid cell detects an abnormality and reports the abnormal information to activate its one-hop neighbor nodes. As shown in the Fig. 9(a), the green nodes are the one-hop neighbor nodes activated by the central head node, and the red nodes are the set boundary nodes of the dangerous area. Our goal is to find the set red boundary nodes and monitor the entire danger zone. The boundary nodes of all green nodes are determined with the step size of 10 as shown in Fig. 9(b). Because the green boundary nodes are in the region surrounded by the red boundary nodes, that is to say, they are abnormal nodes and need to activate their one-hop neighbor nodes again to detect the abnormal situation. We turn the activated nodes into blue and use green nodes to represent the newly activated nodes. So the neighbor nodes of the one-hop abnormal boundary nodes change from the sleeping state to the activated state, which are called two-hop neighbor nodes. The green nodes represent newly activated neighbor nodes. The red boundary nodes are still not found, so it is necessary to continue to activate the neighbor nodes for detection. Look for the boundary nodes in the same way, and get the results as shown in Fig. 10. The newly activated neighbor nodes in Fig. 10(a), namely the three-hop neighbor nodes and it is slef-defined, cannot completely contain the entire dangerous area. Thus, one-hop neighbor nodes of these boundary nodes need to be activated again, and the result as shown in Fig. 10(b). From this figure, we can know that the whole set danger area is completely included by activated nodes. Specifically, the red boundary nodes are surrounded by newly activated nodes and the extent of the contaminated area is determined. Fig. 9(a), Fig. 9(c), Fig. 10(a) and Fig. 10(b) show the entire processes of the method of AONN. The whole danger area is determined by constantly activating one-hop neighbor nodes of abnormal boundary nodes until the normal nodes are detected.

(iii) Cloud Model-IoT Sensing Network Collaboration (CM-IoTSNC)

The atmospheric dynamic diffusion model in the cloud can simulate the approximate diffusion range and trend of toxic gases after receiving the leakage source location information and meteorological information forwarded by the backbone node. The cloud transfers the boundary location of the dangerous area to the IoT nodes, as shown the red nodes in Fig. 11. In order to modify the boundary of the dangerous area, these boundary nodes activate their neighbor nodes that in the sleeping state within communication range, such as the blue nodes in the figure.

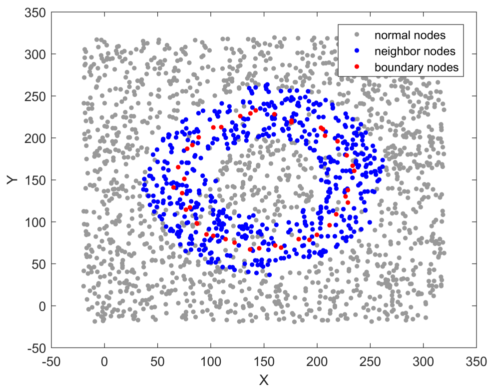



**FIGURE 11.** The coordinate graph of the method of CM-IoTSNC.

The method can predict the diffusion trend of toxic gases in ideal and complex environments, which predict through the model deployed on the cloud after sensing an abnormal situation. On the one hand, the number of activated nodes and the amount of information transmitted between nodes are small, which can greatly reduce the network energy consumption; on the other hand, the results of prediction can guide the staff to make plans in advance to reduce casualties and losses. The method can largely compensate for the shortcomings of current monitoring technology and enables efficient monitoring.

## V. RELATED WORKS AND COMPARISON

### A. GAS DIFFUSION STUDY

The leakage and explosion of toxic gases not only cause huge economic losses, but also have a serious impact on the surrounding environment and human health. Such accidents are highly harmful and difficult to handle. Therefore, it is important to study the gas diffusion law and the gas concentration distribution. The most representative of the gas diffusion models is Gaussian model. On the basis of Gaussian model, many diffusion models are established by improving this model. In [28], the authors propose a new Gaussian dispersion model, which is a plume rise model that takes into account the position of the chimney relative to the building, and is developed for plume rise and building downwash during the diffusion process. By using the numerical plume model to estimate the plume trajectory, the turbulence intensity and wind speed can be calculated. Researchers add the terrain factor to the Gaussian plume model in [29]. The gas leakage simulate system is developed by using geographic information system technology. The accuracy of gas diffusion model is improved by combining the simulated urban area. Due to the diversity of urban terrain, the calculation is complex. The authors propose a method to simulate the diffusion of radioactive gas using geographic grid. Considering the complex geographical environment, that is, the comprehensive effects of wind field, terrain surface, dry deposition and decay of gas on atmospheric diffusion concentration are fully considered. A dynamic visualization model of gas diffusion is achieved by improving the Gaussian model [22].

### B. METHOD FOR DETECTING CONTINUOUS OBJECT BOUNDARY

The size of continuous object is generally larger than the size of individual object, and multiple sensor nodes are usually required for detection continuous object. This means that in the process of monitoring continuous objects, multiple sensor nodes or even all nodes transmit data at the same time. That is to say, individual object detection and tracking protocols are no longer suitable for detection and tracking of continuous objects. Therefore, it is very important to develop a reasonable scheme to monitor continuous objects, so as to minimize the energy consumption and maximize the lifetime of the network. In view of the toxic and radioactive gas leakage and diffusion considered in this paper, the most important things are to determine the hazardous areas and locate the boundary of the hazardous areas immediately and accurately.

In [8], Jin *et al.* proposed the concept of boundary node and an energy-efficiency continuous object tracking protocol. The algorithm automatically adjusts the sensing range of nodes to identify whether it is a boundary node or not, instead of exchanging information between neighbor nodes. Such an approach reduces the energy consumption of mutual communication between nodes. Finally, the backbone node can estimate the position and shape of the target by analyzing the subset of the boundary nodes. In [30], Luan *et al.* proposed a scheme based on ring architecture for tracing continuous objects in WSNs, that is, ring-based continuous object tracing. The sensor is used as a ring to detect the target. Based on the ring structure adopted in this paper, the location of target boundary information can be calculated, but not the boundary node. The method effectively reduces the energy consumption and improves the accuracy of target detection.

Authors proposed a dynamic cluster structure for continuous object detection and tracking in sensor networks. In order to reduce the communication cost, the boundary sensors are grouped into several clusters. The local boundary information in the cluster is fused, and the locally integrated boundary information is sent to the sink through the cluster head. By comparing the state between the boundary nodes and its neighbor nodes, we can know the boundary of the object. If neighbor sensor nodes detect the object, those neighboring nodes become boundary sensor nodes [31]. The method avoids transmitting redundant information and reduces communication cost. In [32], authors proposed a new algorithm named continuous object detection and tracking. The energy consumption is mainly reduced by decreasing the number of boundary nodes and uploading information. In this algorithm, when an object is expanding, only the nodes in the outer region of the phenomenon become boundary nodes. Similarly, when an object is shrinking only the nodes in the inner region become boundary nodes. Instead of internal and external nodes acting as boundary nodes at the same time, this reduces the number of boundary nodes. At the same time, a new method of data reporting is proposed. The node that receives the most phenomenon changed message from boundary node is selected as the representative node, and uploads the data to the receiver. This method reduces the communication cost of the whole algorithm.

Ping *et al.* proposed a two-stage boundary face detection mechanism. When a potential event occurs, planarization algorithms are used to construct a coarse face of continuous objects. Different algorithms should lead to different topologies in the boundary detection phase. This paper uses four kinds of planarization algorithms, which are gabriel graph [33], relative neighborhood graph [34], yao graph [35] and k-localized delaunay graph [36]. The experimentally shown that the k-localized delaunay graph planarization algorithm can obtain a more accurate boundary faces. On this basis, the spatial interpolation method are used to estimate the sensory data of sensor nodes in the boundary face. When the perceptual data indicates that they may be more suitable as candidate boundary nodes, then the corresponding face nodes are awakened and the fine boundary faces are made [37]. This method can get fine boundary, but the assumptions of the planarization algorithm are not applicable to all cases.

## VI. CONCLUSION

For continuous events such as toxic gas leakage and diffusion, boundary detection of target objects is an important research challenge. With the rapid development of the IoT, it is a reality to combine the IoT to monitor and detect the occurrence of potential events. This paper proposes a novel method of CM-IoTSNC, which can predict gas diffusion trends in ideal and complex environments by utilizing the powerful computing power of the cloud. Compared with other two methods of WSM and AONN, the energy consumption during the whole detection processes are calculated to measure the quality of the adopted methods. According to the energy consumption results, the method proposed in this paper consumes the least amount of energy and achieves better results, and can guide the staff to make planning and deployment in advance. In the future work, we will focus on studying real-time perception on cloud and adjusting diffusion model according to prediction results.

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