# Wireless Sensor Based Criticality and Localization of Gas Leakage Detection and Estmation

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***Abstract*:**

*In this new era, businesses confront major challenges, notably in the petroleum industry's management of flammable products. Micro-sensing sensors in WSNs (Wireless Sensor Networks) may detect and gather data for analysis, then wirelessly transmit it to their controller. Pipeline distribution reporting is tracked using a machine-learning method. This work presents a design method for an intelligent WSN for gas leak detection and criticality estimation in pipelines with anomaly fluctuation for gas or oil transportation. The 'NPW (Negative Pressure Wave),' which is measured by each individual sensor in the network, is analyzed using machine learning. Kernel-based models (Generalized Regression Neural Network enhanced advection-diffusion model) are used to assess the criticality of leakage, location, and release rates. The simulation results produced by the suggested method, when compared to current estimating methodologies, show promise in various noise percentages.*

***Keywords* -** *WSN; Machine Learning; GRNN; Gas Leakage;*

# I Introduction

Many real-time applications have been developed in recent years in a variety of sectors. These apps are created in such a way that they intelligently interact and handle things [1]. In addition, in recent years, the employment of wireless communication devices and sensor advancements for temperature measurement, acoustic detection, seismic detection, and other purposes has grown widespread [2]. This paper outlines a method for preventing gas leaks throughout the screening and elimination processes. Gas leaks can occur for a variety of causes, including defective appliances, rusted and aged pipelines, and their weak couplings. If not controlled, the leakage of Liquid Petroleum Gas (LPG) and other natural gases might result in an explosion. Gas leakage may not always be noticed, putting many lives at jeopardy [3]. In both closed and open spaces, methane gas, which has a disagreeable odour, will identify itself. Humans should be evacuated from a specific region before the explosion is triggered. To address these risks, the United States approved the Pipeline Safety Improvement Act in 2002, which required annual inspections to assure safety, particularly for companies handling natural, toxic, or explosive gas [4]. Not only people, but also the environment, suffered as a result. The management of gas leakage was divided into two categories: Grade-I and Grade-II. The gas that poses a threat to people or property is classified as Grade-I, requiring immediate attention and repair, whereas the gas that has no effect on anything at the time of leaking is classified as Grade-II, requiring a repair timetable [5]. WSNs (Wireless Sensor Networks), which are utilised in a variety of applications, are now being upgraded. Gateways and sensors are being developed to help usher in a new era of technology and data collection for sophisticated statistics [6]. Despite its flaws, the WSN was implemented with specific considerations such as the number of nodes necessary in the deployment, the size of the region to be watched, the signals to be sensed, the signs to be relayed, and the power standby needs [7]. Even if all of these factors are taken into account, there will always be a constraint that can be overcome using AI (Artificial Intelligence) or other uncertain methods [8]. The machine learning algorithm, on the other hand, can deal with the unpredictability of the problems that need to be solved. The Machine Learning method is used to operate several applications in various fields intelligently [9]. The important tasks of ML algorithms are regression, classification, uncertain approximation, and estimation. In the WSN Phase, there is a requirement for environmental/data adaptability, which varies with time, as well as the ability to collect new information for the purpose of developing significant knowledge [10]. The mainframe of the WSN, as well as its controlling nodes, should learn to run efficiently in terms of power usage. For an efficient operation, the calibration should be managed and handled in relation to changes in data values [11]. Due to the unknown nature of the location, researchers find it challenging to execute the mathematical model and construct a linear system. WSN systems can gather and manage large volumes of data, and they should have a vital feature extraction method to reduce computation complexity [12]. The points made above demonstrate the need for machine learning that is strengthened by the WSN. In recent years, a slew of new approaches for dealing with water or any other liquid leaks have been introduced [13]. These approaches were created in response to a change in the hydraulic system's status induced by a sudden leak or explosion. However, these solutions may encounter issues like as inaccuracy and missing data, making the process more difficult to handle. It can sometimes result in false alarms [14].

Section II contains some previously formulated related works. The Advection-Diffusion model, which has been successful in recent times, is explained in Section III. The Leakage Detection Phase is detailed in Section IV. The machine-learning formulated work intended to be employed with the ADM is presented in Section-V. Section VI contains the Implementation Strategies, and Section VII has the simulation and outcomes of the planned work, as well as a relevant comparison.

## II Related Works

Many ways for detecting and managing gas leaks have been developed in recent years. The methods described below are among the most important. A Fusion Centre is utilized to gather data from tanks or containers in the traditional method, and then statistical algorithms are employed to evaluate the data [16]. The source parameters for statistical analysis were estimated using this method. P.Karthigamanathan et al. (2002) presented a Source term estimation of pollution from an instantaneous point source [17], in which the gas concentration was recorded at several instant points and the parameter estimation was inferred using an inverse model. V N Christopoulos and S Roumeliotis (2005) proposed "Multi-robot trajectory generation for single-source explosion parameter estimation," which required the robot to move back and forth and pick up a specific location in order to estimate and determine the source parameters that defined the container leakage or damage [18]. This technique was created using the Particle Swarm Optimization approach, in which birds seek food in a random location, causing systems to migrate towards an optimum solution. S. Mahfouz, F. Mourad, and colleagues (2014) proposed "Machine learning and Kalman filter-based target tracking using WSN," in which the author used pre-processed data (using the Kalman filter) for machine learning and reduced a large number of target tracking features to a few significant elements [19]. When it comes to tank leaking, this methodology has been shown to be the most effective method for orienting the estimation. "Decision techniques for source identification and restoration in parametric convolution," developed by G. Delmaire and G. Roussel (2012), used a single remote sensor to estimate pollutant flow [20]. In this technique, the 1-D context was coupled with conditional deconvolution, which necessitated the use of previously collected data. In "Information fusion for wireless sensor networks," E. F. Nakamura, A. A. F. Loureiro, et al. (2007) employed several sensor clustering approaches, both centralized and distributed, resulting in a huge amount of expensive power supply necessary to keep the process going. There was not just a waste of power, but also a waste of bandwidth [21].

The Advection-Diffusion Model and a machine learning algorithm are combined in this article to create an effective leakage management system.

## III Advection-Diffusion Model

The advection-diffusion model was developed by P. Karthiramanathan, R. McKibbin, and others in 2002. This improved version of the model can detect changes in gas concentration in real time. When building the advection-diffusion model, keep the following assumptions in mind.

(1) Instantaneous Gases Leakage of $L$ kg

(2) Leakage happens at the location $X_0, Y_0, Z_0$

(3) At time $T_0$
(4) and A wind with mean Velocity $U = (U_X, U_Y, 0)$ which spreads the gas-particle concentration $C$ in the region.
The Mass Conversion controls these parameters is given by
$\frac{\partial C}{\partial T} = -\nabla q$ (1),
whereas the gradient operator $\nabla$ and $q$ is a Mass Pollutant measured per flux unit area is denoted by
$CU - \begin{bmatrix} K_X & 0 & 0 \\ 0 & K_Y & 0 \\ 0 & 0 & K_Z \end{bmatrix} \otimes \nabla C$ (2),
where $CU$ is the average mass of the advection that the wind spreads at a given velocity. The average mass of the concentration is a tensor product of the eddy diffusivities $(K_X, K_Y, K_Z)$ of the concentrated gas in a specific direction $(X, Y, Z)$, therefore the mass of Advection distributed by the wind at a particular velocity is given by,

$\left(C\, U_X - K_X \frac{\partial C}{\partial X}, C\, U_Y - K_Y \frac{\partial C}{\partial Y}, -K_Z \frac{\partial C}{\partial Z}\right)$ (3)

The boundary conditions for determining a gas concentration in a certain region, which is believed to be zero at infinity in the spatial direction, as well as the status of gas not absorbed by the earth, are obtained by combining equations (1) and (3). Furthermore, the parameter is treated as if it were a constant. As a consequence, we've come up with the following solution: As a result, the following solution is created.
$C\,(X, Y, Z, T) = \frac{M_{gl}}{8\pi^{2/3}(K_X, K_Y, K_Z)^{1/2} \Delta T^{3/2}} \times$
$\exp\left(-\frac{(\Delta X - U_X \Delta T)^2}{4K_X \Delta T} - \frac{(\Delta Y - U_Y \Delta T)^2}{4K_Y \Delta T}\right.$
$\left.\right) \times \exp\left(-\frac{(\Delta Z)^2}{4K_Z \Delta T} + \exp\left(\frac{(\Delta Z')^2}{4K_Z \Delta T}\right)\right)$ (4)
Where
$\Delta X = X - X0,\ \Delta Y = Y - Y0,\ \Delta Z = Z - Z0,$
$\Delta Z' = Z + Z0 \text{ and } \Delta T = T - T0$
.
To simplify the assumptions, eqn (4) is simplified as shown below.
$C(X, Y, 0, T) = \frac{M_{gl}}{4\pi^{2/3}(K_X, K_Y, K_Z)^{1/2} \Delta T^{3/2}} \times$
$\exp\left(-\frac{(\Delta X - U_X \Delta T)^2}{4K_X \Delta T} - \frac{(\Delta Y - U_Y \Delta T)^2}{4K_Y \Delta T}\right.$
$\left.\right)$ (5)
The WSN groups sensors in different areas of the gas-filled zone, allowing for the calculation of multiple parameters to check for gas leakage [22]. The Gasse mass and concentration, as well as fundamental terminology, are utilized to locate the leakage. A reference to equation (5) of these terms has been found to be useful in the leak management approach.

## IV Leakage Detection Phase

The suggested approach employs a WSN that employs a variety of sensors to continuously monitor the region for leaks or other hazards. A machine learning method [23] handles each of the three phases of leakage detection: [1] detection, [2] estimation, and [3] criticality classification. **In the process of detection phase**, the sensors are made available in many locations such as $\{X_{N,} \quad YN, Z_{N,}\}$is given by $\{X_{N,} Y_{N,} 0\}$ $\boldsymbol{where\ N \varepsilon \{1, 2 \ldots . n\}}$. The Value $n$depends on the number of sensors used to cover the area. Based on the advection-diffusion model outlined in the preceding section, these sensors give a collection of key aspects of data about time. With this, the gas concentration $C_g$ is assumed to be $C_g\,\{X_1, Y_1, 0, T\}\ to\ C_g\,\{X_n, Y_n, 0, T\}$. To extract the best significant features of the data, the data will be processed under sampled.

## V Generalized Regression Neural Network (GRNN)

Where the Artificial Neural Network (ANN) is utilized, the data obtained from the sensor nodes will have dispersed variances and will not match one another. Many ANN algorithms are used to handle data for different applications. After a thorough examination of the data and its important details using different ANNs, it was discovered that GRNN is suited for this task [26].

The GRNN parameters must be predetermined and mapped into the input and target at first. The GRNN is a supervised algorithm that requires training to reach the goal [27]. The Probability of GRNN is given by

$$T(X) = \frac{\sum_{j=1}^{n} \mathrm{T_j} \exp\left( {-Dv_j^2}/{2_{\sigma^2}} \right)}{\sum_{j=1}^{n} \exp\left( {-Dv_j^2}/{2_{\sigma^2}} \right)} - (1)$$

$$Dv_j^2 = \left(X - X_j\right)^{Th} . (X - j) - \ (2)$$

$Dv_j^2$ is the distance measured between the deviation of the predicted value during the process of training and the training samples.

Case-1: If the value of divergence is high, then the error produced in the particular point is more top.

Case-2: If the $Dv_j^2$ is equal to zero, then this point is considered to be the best fit value in which $\exp\left( {-Dv_j^2}/{2_{\sigma^2}} \right)$ is relatively small or maybe zero. $\mathrm{T_j} \exp\left( {-Dv_j^2}/{2_{\sigma^2}} \right)$ Indicates the interaction in which the training is preceded. σ is the standard deviation calculated for the data point, which is responsible for adjusting the correlated points towards smoothness.

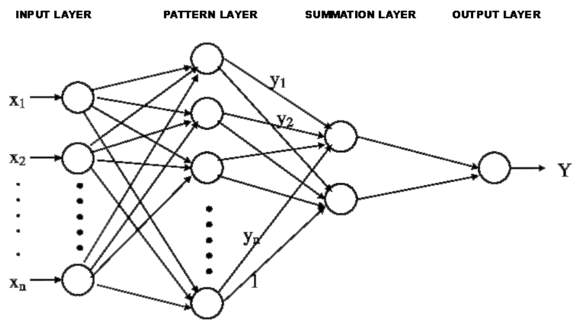


**Figure-1:** Neural arrangement of GRNN

Unlike traditional artificial neural networks (ANNs), the GRNN includes four layers: an input layer, a pattern layer, a summation layer, and an output layer. To map input values to goal values, the GRNN method, like other ANNs, goes through a consolidation and mapping phase. We need data from the issue in question, in this instance the Advection-Diffusion Model and related gas leakage estimation, to train the GRNN. The input layer collects the data for the training process. To understand their pattern, the second layer calculates the distance between the data vectors and the activation function's activity.

In the following phase, the numerator and denominator are combined to reduce production values to factors. Finally, the output layer calculates the output using the pattern and summation layers. Because this is a supervised learning approach, the data is divided into input and target for the classification phase. To decide which era is the best, the MSE (Mean Square Error) is utilized. As a result, the GRNN is used in the learning and planning process.

## VI Strategies of Implementing

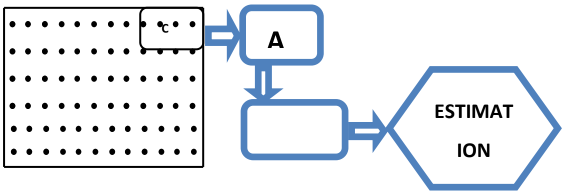


**Figure-2:** Systematic Process of Leakage Detection and Criticality Estimation

To Estimate the criticality and to check the location of the leakage, various clusters of WSN and the sensors is being kept in different places. The main objective is to identify the location of the gas leakage and categorize the criticality of the $M_{gl}$ (i.e., Gas Release mass) and its hazardous concentration.

1. Depending on the scale of the system, the WSN provides for a large number of sensors, nodes, cluster heads, communication devices, processing devices, machine learning-enabled GPUs, and other components, all of which allow for quick detection and estimation system change.
2. Trained data is obtained and given as inputs for the GRNN's input layer, which is then mapped to the hidden layers and neurons to match the stated targets.
3. Because GRNN is a supervised learning technique, the mapping process' regression strategy will correlate points that are connected and close to one another while ignoring points with significant disparities.
4. A trained network will be constructed based on the trained data obtained during the training or learning process, which will be used to make future choices.
5. The estimating step begins when the above-mentioned classifier makes a decision, as illustrated below.

## V Estimation Phase

While preceding parts covered the detection and classification phases, this one concentrates on the estimation stage. During the hazard-watch operation, the sensors are divided into clusters and kept under the control of a cluster head. Whenever a hazard is caused by a gas leak, the cluster that is most viewable will be identified. During the hazard-watch period, almost every cluster may generate an alert. If the WSN coverage is particularly strong, identifying the individual cluster will be difficult. The estimation will be done in this case by analyzing close clusters separated by the same boundary.

These neighboring groups will be checked by adjacent grouping sensors. Sensor group vectors are used by the system to identify a variety of gas emissions. This approach is calculated using the greatest advection-diffusion factor, which offers information on the location of the explosion and the common boundary between the sensors. The local maxima are calculated in the following deep segment to determine where the danger is occurring inside the cluster. This method has a propensity to expand its nature in order to evaluate higher concentration ratios.

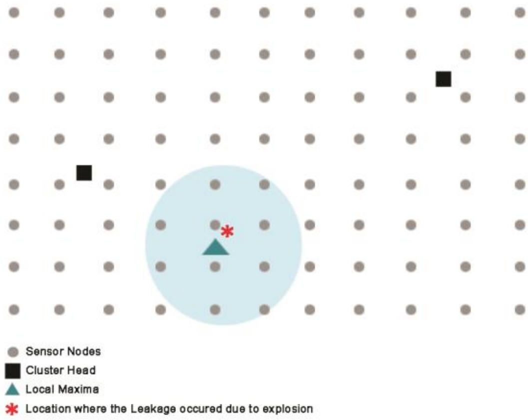


**Figure-3:** Sensor's nodes in the cluster in the mission to detect and estimate the leakage.

After the concentration reached its maxima, the cluster starts collecting the information about the process. Instead of processing data from all of the sensor clusters, the procedure looked at the data from each cluster's Sensor Head. The evaluation of the trigger of local maxima will be constantly followed, as shown in fig.3.

The illustration process is depicted in Figure 3 with a limited number of sensor nodes. The hazard zone is defined as the area with the triangle mark, where local maxima are higher than elsewhere.

## VI Simulation and Results

The GRNN networks are created with appropriate knowledge before the systematic process is applied in real-time. In this situation, the classification training is carried out with the help of pre-defined data that feeds the classification process. The WSN data values are advection-diffused to a factor as the input for the ANN and the criticality level as the target for the GRNN, such that after the training process, the GRNN produces an approximation of the criticality that is used for classification and subsequent action. The following are the GRNN's performance factors:

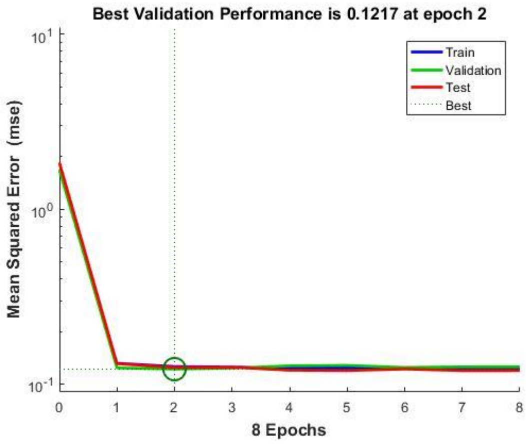


**Figure-4:** Performance evaluation in the GRNN training

To achieve the optimal performance curve, GRNN is trained to estimate the criticality of gas leakage. The iteration was about to run for 1000 times to achieve the best performance curve. Fig.4 shows the best performance curve made. While doing the training process, The trained data is categorized into three sections namely training data (70%), testing data (20%) and validation data (10%).

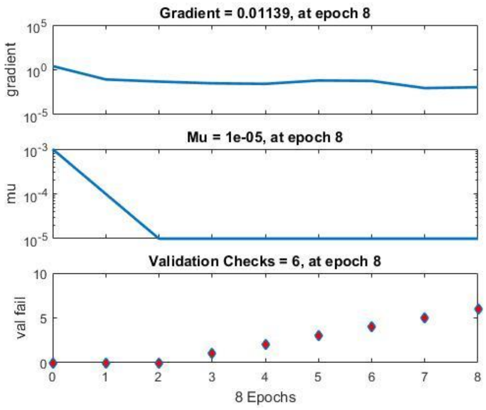


**Figure-5:** Training state of the best performance network

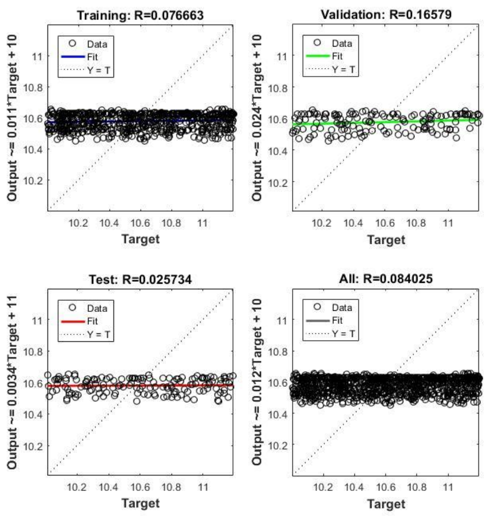


**Figure-6:** Regression ratio achieved

The real-time classification is processed, and the criticality is examined, using the trained network. Once the leak has been confirmed in the estimating step, the designation will look for the spot that requires attention.

**State-of-the-art systematic process**

To show the state-of-the-art systematic method, the error percentage produced is compared to existing algorithms with noise percentages ranging from 1% to 5%. Throughout the measurement procedure, the area is taken into account for analysis. The field analyzed $X_0$ &$Y_0$ is the location of the sensor where $M_{gl}$ its release rate is measured, and this procedure of estimating concentration measurement is dependent on it. The following are the outcomes:

**Table I: Comparison on EM [17] and PM based on the Error in percentage**

| Noise | Methods | $\hat{M}gl$ | $\hat{K}_X$ | $\hat{X}_0$ | $\hat{Y}_0$ |
|---|---|---|---|---|---|
| 1% | PM | 0.5696 | 0.0168 | 0.018 | 0.0356 |
| | EM | 4.8 | 1.2 | 1.42 | 0.72 |
| 2% | PM | 0.79 | 0.0167 | 0.0184 | 0.018 |
| | EM | 10.32 | 2.49 | 2.67 | 1.246 |
| 3% | PM | 0.963 | 0.0186 | 0.0182 | 0.0366 |
| | EM | 14.54 | 3.46 | 4.521 | 1.988 |
| 4% | PM | 1.464 | 0.0365 | 0.0137 | 0.037 |
| | EM | 19.69 | 4.61 | 5.25 | 2.48 |
| 5% | PM | 1.699 | 0.0361 | 0.0176 | 0.064 |
| | EM | 21.524 | 6.876 | 6.32 | 3.621 |

Where EM [17] refers to an existing technique (Advection-Diffusion Model) that does not employ a machine learning algorithm, and PM refers to a proposed method (GRNN enhanced Advection-Diffusion Model for gas leakage estimation).
$\hat{M}gl$ is a gas release mass, $\hat{K}_X$ eddy diffusion, $\hat{X}_0$ and$\hat{Y}_0$ location of the leakage or explosion.
As a result of the comparison, variation noise has no influence on the suggested approach (A Generalized Regression Neural Network augmented with the Advection-Diffusion Model for gas leakage prediction) or the existing procedure (advection-diffusion Model without any machine learning enhancement). The proposed approach, in comparison to the present method, produces the least amount of inaccuracy.

## Conclusion

Using a machine-learning-based advection-diffusion methodology supplemented with WSN, this work offers a novel clustered method of systematically processing the detection and assessment of the criticality of gas leakage explosions. The positioning system is also described, which is based on the use of WSN and sensor clusters. It is straightforward to make an uncertain judgement using this technique, which is based on intelligent computing and the GRNN. The simulation results demonstrate that this technique yields favorable outcomes. The purpose of this study is to identify a number of leakage sources and establish their criticality, kind, and location. Even the risk assessment will be geared toward improvement.

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