Digital Model of Automated Mobile Reconnaissance Robot with Artificial Intelligence

Sabyrzhan K. Atanov[1], Hüseyin Canbolat[2] and Zhexen Y. Seitbattalov[1]

[1]L.N. Gumilyov Eurasian National University (ENU), 2 Kanysh Satbayev St, Astana, Z01A3D7, Kazakhstan
[2]Ankara Yildirim Beyazit University (AYBU), Gazze Cd. No:7, Ayvali, Keçiören, Ankara, 06010, Turkey

Abstract
Modern mobile robots are used in various tasks from the simplest to the most complex, requiring a high level of automation and the use of artificial intelligence. The use of mobile robots helps reduce the risk for emergency workers and the risk of exposure to human factors. Special cases of using mobile robots are reconnaissance of areas affected by chemical, biological, radiological and nuclear (CBRN) disasters. Our work proposes a model of an automated mobile reconnaissance robot using artificial intelligence to identify obstacles and evaluate environmental damage. As a result, digital and fuzzy logic models were developed, which made it possible to evaluate the effectiveness of the proposed design of a mobile robot and solve the issue of automating the control of the robot.

Keywords
Reconnaissance robot, autonomous navigation, CBRN threats, GPS, webots

1. Introduction

The scope of mobile robot applications is quite widespread today. Mobile robots are used in both civil and military fields, namely from delivery to performing complex operations with artificial intelligence in areas that are difficult to access or in dangerous environments for humans [1]. For example, a mobile robot sprinkler of the Fregat system was considered in one of the studies [2]. Currently, the largest amount of research using mobile robots is found in the field of search and rescue operations after a disaster [3]. For instance, one of the studies proposed a special design of a mobile robot with an active articulating chassis capable of functioning in conditions after an earthquake or landslide to search for people [4]. In other research, a spherical shape is considered to ensure the high mobility of the robot and access to hard-to-reach places [5]. Mobile robots are also used in fire-hazardous environments to reduce losses among firefighter personnel [6]. A fairly relevant use of mobile robots is being considered for evaluating the damage to the area after chemical, biological, radiological and nuclear (CBRN) disasters [7, 8, 9]. Unmanned aerial vehicles (UAV) are used for detecting high-lying targets and reconnaissance objects [10]. Particularly extreme operating conditions for a mobile robot are space conditions [11].

An open issue in mobile robots remains the problem of optimizing path planning [12, 13]. A similar question is relevant for planning the path of a lifted object by a manipulator [14]. The Global Positioning System (GPS) is used to locate and designation of an intelligence target or object. [15]. Also, one of the tasks often solved along the way during reconnaissance is drawing up a map of the open or indoor area [16]. If we consider the use of mobile robots in the security field, then most robots are used to detect and pursue intruders [17, 18].

The purpose of this paper is to develop an automated mobile robot with artificial intelligence for conducting reconnaissance in conditions of chemical hazards, capable of identifying obstacles and measuring environmental pollution indicators.

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atanov5@mail.ru (S.K. Atanov); huseyin.canbolat@gmail.com (H. Canbolat); sbtl.jeks@gmail.com (Zh.Y. Seitbattalov)
0000-0003-2115-7130 (S.K. Atanov); 0000-0002-2577-0517 (H. Canbolat); 0000-0003-2607-4908 (Zh.Y. Seitbattalov)

2. Materials and methods

Webots R2023b was selected as the robot simulator [19] for creating a path-planning algorithm for a mobile reconnaissance robot due to its extensive range of uses. It enables controller programming, boasts a vast repository of robots and tools for designing them, and supports numerous commonly used programming languages. Additionally, it is a versatile, cross-platform software.

Among the available robots in the Webots platform, the Pioneer3 has been selected as the mobile reconnaissance robot for operations in chemically challenging environments. Figure 1 displays the mobile reconnaissance robot that has been designed for this purpose.

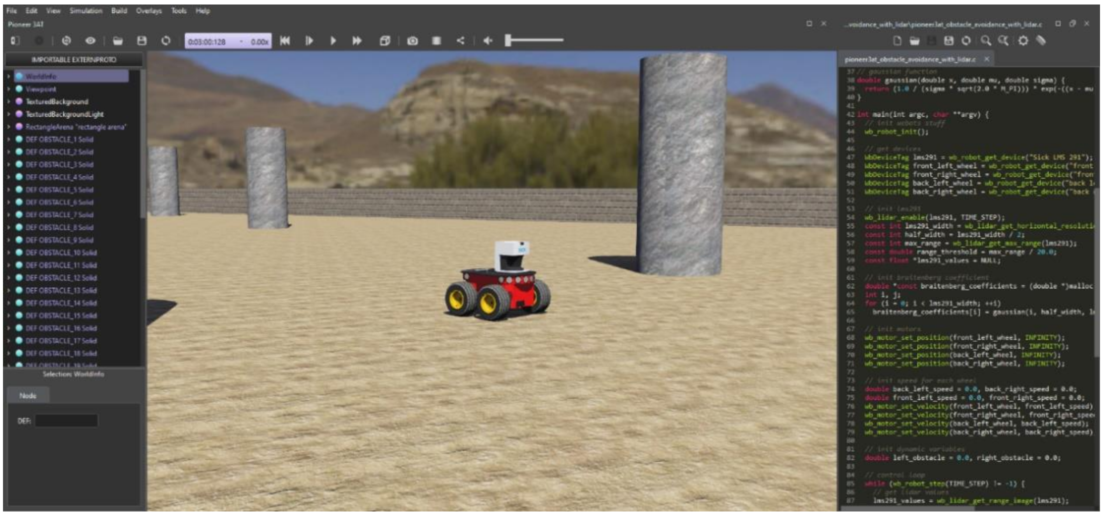

Figure 1: A designed mobile reconnaissance robot in Webots

The robot contains lidar sensors, GPS, a Wi-Fi module and a gas analyzer, as well as a camera and a computing device for applying algorithms and artificial intelligence. The route for reconnaissance can be specified via GPS coordinates, or the robot can randomly reconnoiter the area using lidars to detect and avoid obstacles along the reconnaissance path.

Fuzzy logic was chosen as a method for measuring environmental pollution. The MATLAB programming language was chosen to implement its knowledge base and interface.

Further, we have proposed a general scheme of the system with a description of the reconnaissance process in the damaged area.

2.1. General scheme

Figure 1 illustrates a conceptual diagram of how a mobile reconnaissance robot conducts reconnaissance in an area affected by chemical and radiological disasters, serving as a representation of the process in a real-life scenario.

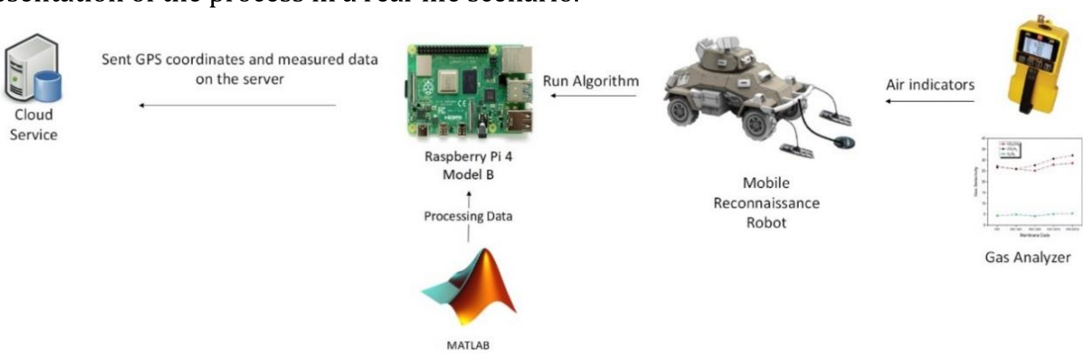

Figure 2: The general scheme of reconnaissance by a mobile robot

The gas analyzer measures the ambient air value and transmits the data to the Raspberry Pi of the mobile robot. A single-board computer stores a knowledge base and a fuzzy logic-based algorithm compiled in MATLAB to estimate the level of air pollution and threat to human life. The result and solution are sent to the cloud server via a secure communication channel. As other studies have shown, the Raspberry Pi 4 Model B copes well with solving problems connected with artificial intelligence and complex computing tasks [20, 21, 22].

2.2. Gas analysis process

In order to create the air quality estimation model, it was essential to gather data on oxygen, methane, carbon dioxide, and chlorine levels for the assessment of air pollution. We received data from the gas analyzer, which is presented in Table 1.

Table 1
Air Quality Scale

Levels of air pollution	Oxygen	Methane	Carbon dioxide	Chlorine
Safely	10 %	2 %	1,5 %	0,006 %
Dangerous without protective measures	20,5 %	higher than 2 %	3 %	higher than 1 %
Lethal dose	50 %	over 5 %	over 5 %	Over 3 %

All fuzzy operations were conducted within the Fuzzy Logic Toolbox of MATLAB. You can observe the input and output data in Figure 1.

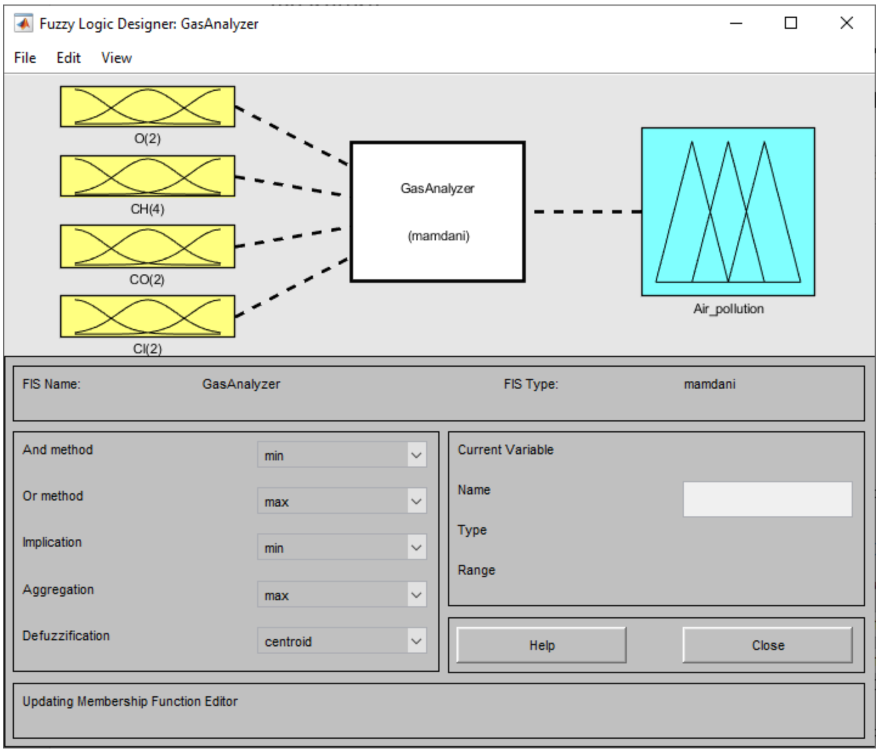

Figure 3: Designing fuzzy inference system

The two most commonly employed Fuzzy Inference Systems are Mamdani and Sugeno. Although the fundamental components of these Fuzzy Inference processes are similar, the distinction between Mamdani and Sugeno lies in the output [23]. The Sugeno type establishes the output membership function as a constant or a linear value, whereas the Mamdani type characterizes the output as a fuzzy set. When developing the evaluation model for a gas analyzer, opting for the Mamdani Inference System would be the most suitable choice, given the non-linear nature of indicators related to the content of specific elements in the air and their impact on humans.

To describe element levels in the air and its impact on humans has been used a normal distribution or also known as Gaussian distribution. Figure 1 displays graphical representations of the membership functions for oxygen levels. As noted in Table 1, the oxygen content in the air is about 0.1 or 10 per cent optimal for humans. Above 0.1 is also acceptable up to a limit of 0.35. A higher oxygen content in the inhaled mixture leads to oxygen poisoning.

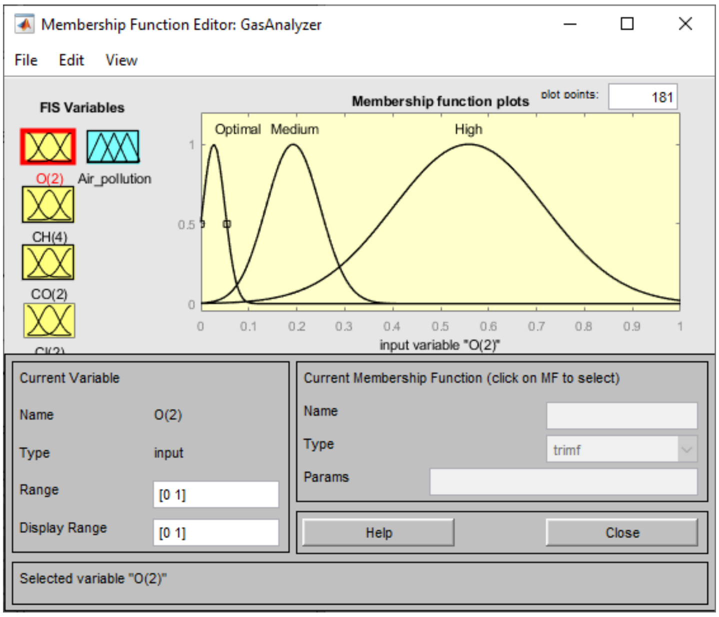

Figure 4: Membership function plots of oxygen levels

In Figure 1, you can find graphical representations of the membership functions for methane levels.

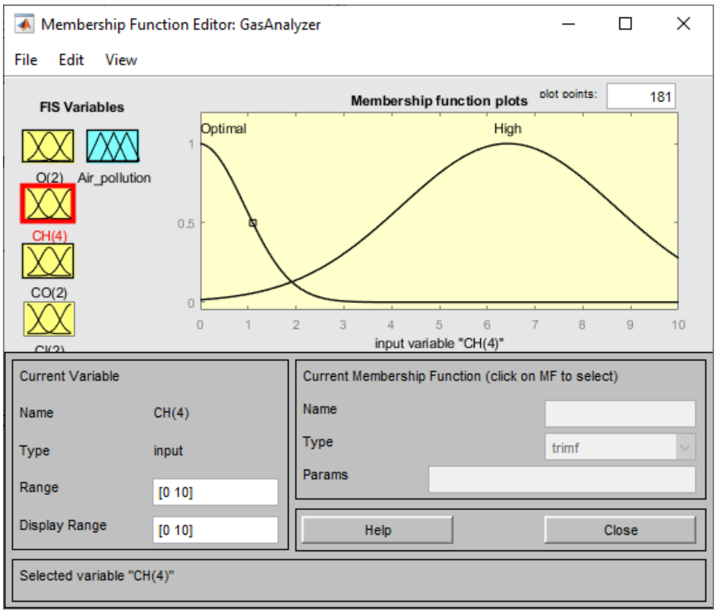

Figure 5: Membership function plots of methane levels

A methane content of less than 3 percent in the air is not hazardous to humans. A higher methane content leads to hypoxia (oxygen starvation), and such a mixture also becomes explosive.

Figure 1 showcases graphical representations of the membership functions for carbon dioxide volume.

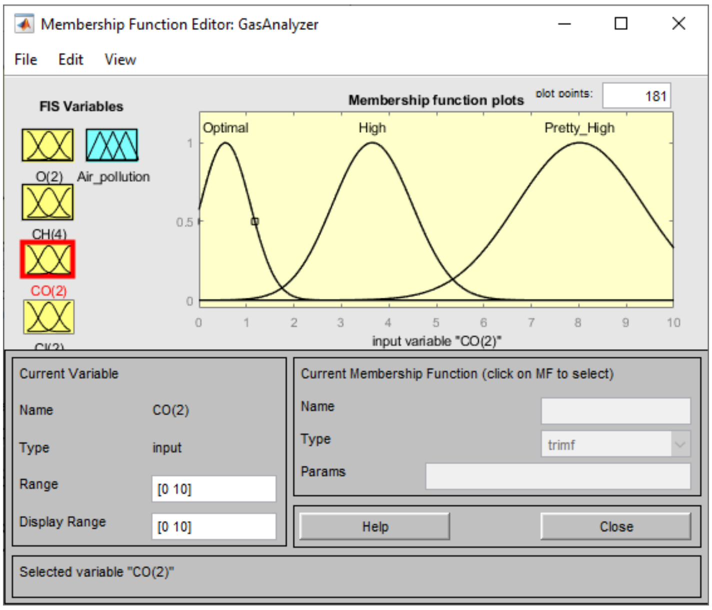

Figure 6: Membership function plots of carbon dioxide levels

A carbon dioxide content of less than 2 in the air is optimal. Carbon dioxide levels reaching around 3.5 lead to headaches and loss of consciousness. Carbon dioxide levels above 6 leads to death.

Figure 1 provides graphical representations of the membership functions for chlorine levels.

Figure 7: Membership function plots of chlorine levels

Chloride is a poisonous gas, up to a value of 0.002 with short-term contact the negative impact on humans is minimal. At higher concentrations and prolonged exposure, it is fatal.

Figure 1 displays graphical representations of membership function plots for air pollution in the output data.

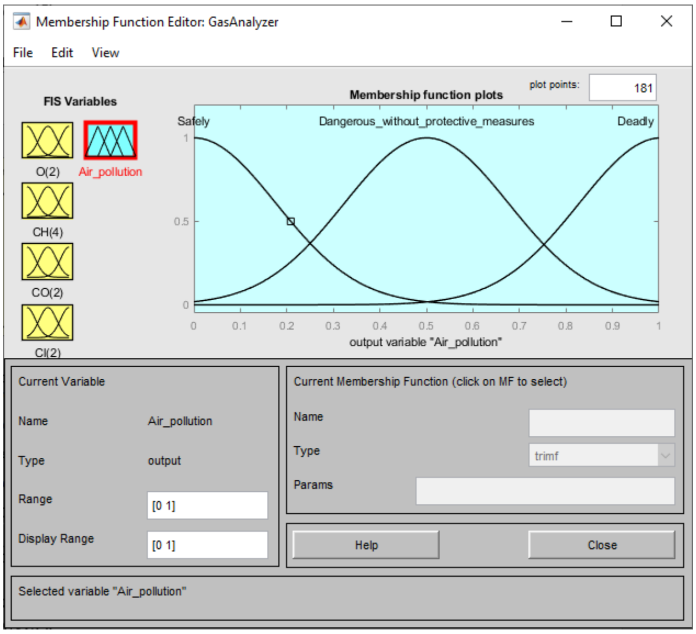

Figure 8: Membership function plots of air pollution

This output parameter is determined by three normally distributed graphs with varying degrees of air pollution and its impact on humans: safe, dangerous without precautions and fatal.

In particular, when considering a case requiring precautionary measures, it can be noted that a person needs to use personal protective equipment and chemical protective suits to reduce the impact of a negative factor on his health.

To fully define the system, it was essential to input the following twelve rules into the rule editor, as depicted in Figure 1.

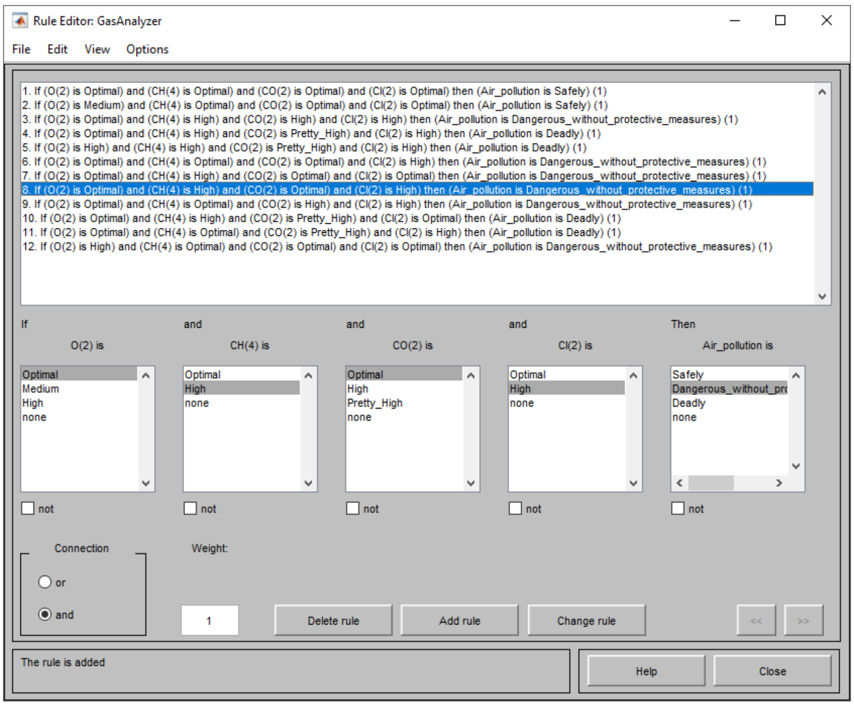

Figure 9: Rule base in MATLAB

To form rule base, the main scenarios and various combinations of input parameters with the "AND" operator were considered and the output result was generated based on that.

Thus, to generate a wider rule base and append more input parameters, the user can add new elements and gases to the fuzzy inference system, indicating the membership function plots and assessing the degree of exposure to a certain concentration on a human. After adding new parameters and membership functions, he can create new rules and their combinations to form an assessment of the impact of these gases on the degree of air pollution.

3. Results

After conducting the simulation, a rule viewer is depicted in Figure 1, illustrating the input and output parameters, as well as the rules applied. In this particular instance, the oxygen level is at 0.5, methane is at 5.5, carbon dioxide stands at 6, and chlorine is measured at 0.008. The resulting air pollution output is approximately 8.2, signifying a significant degree of air pollution, reaching a level that poses a lethal risk to human life.

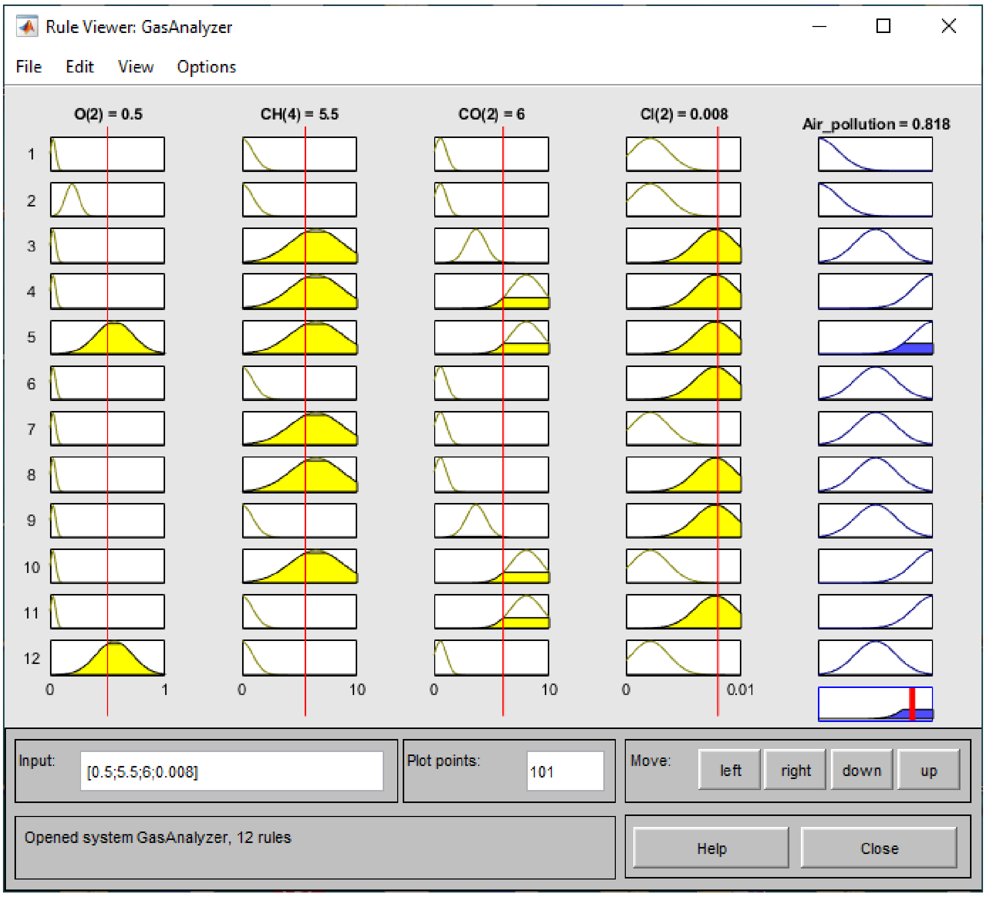

Figure 10: Rule viewer for gas analyzer

Figure 1 illustrates the surface of air pollution, on the x axis is shown the chlorine levels and on the y axis – oxygen level. As can be seen from the surface graph, an increase in the level of chlorine content increases air pollution with the consequence of a threat to life. In turn, oxygen deficiency also increases the chances of death for a person.

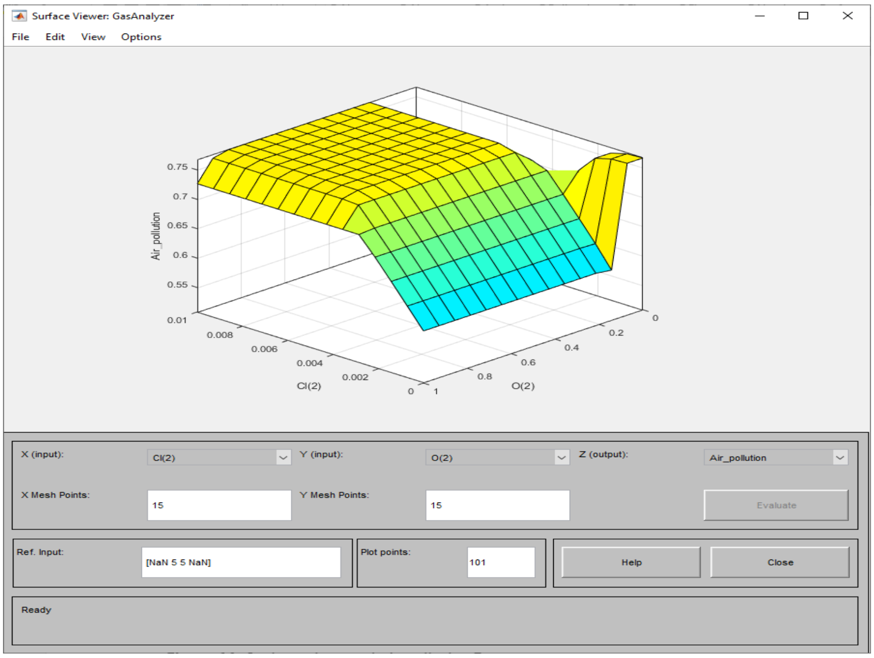

Figure 11: Surface viewer of air pollution

If instead of the oxygen level we take the carbon dioxide content, then the pattern will be approximately the same as on the previous surface, as shown in Figure 1.

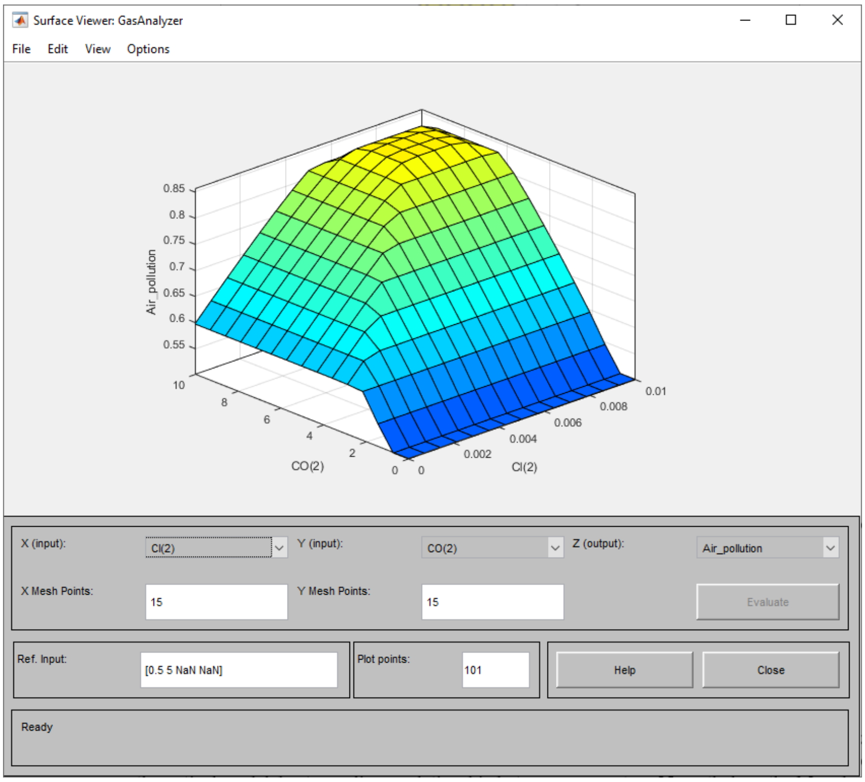

Figure 12: Surface viewer of air pollution

4. Conclusion

The proposed intelligent system based on a model using fuzzy logic allows the user to determine the degree of air pollution with toxic substances and eliminate the negative impact on emergency personnel. It is worth noting that creating an accurate mathematical model for this task was challenging due to the nonlinear relationship between various parameters. However, the Mamdani-type fuzzy inference system has successfully defined the dependency between different chemicals and elements and the extent of exposure to specific gas concentrations on the human body.

Analyzing the surfaces that determine air pollution levels reveals a clear correlation between increased concentrations of toxic substances and the risk of fatalities. In this manner, fuzzy logic control has identified the optimal gas concentrations for different scenarios and their impact on human health to prevent fatalities. The program also allows users to input new data for additional gases and chemical elements.

A general exploration scheme was also developed to determine the concentration of harmful gases and an algorithm was proposed for automated exploration of hazardous areas.

For future research, we are considering adding a dosimeter and signal spectrum analyzers to determine radiation exposure and analyze radio waves.

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