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*Article*

# Smart Carbon Capture System

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**Abstract:** The adaptive and effective carbon mitigation strategies are needed because atmospheric $CO_2$ levels have been increasing very quickly since the start of the Industrial Revolution. The paper introduces a Smart Carbon Capture System which combines post combustion carbon capture with Internet of Things (IoT) technologies to support the automation of the control system, real time monitoring and prediction of emission. This system uses gas sensors, flow sensors, pressure sensors, voltage sensors and current sensors connected to the Raspberry Pi Zero 2W, to monitor $CO_2$ levels, energy consumption and storage conditions continuously. A vacuum air pump is controlled adaptively using the Pulse Width Modulation (PWM) signal that is generated according to the detected $CO_2$ concentration. This is a linear regression model that is light (because of NumPy's polyfit function) and predicts short time emission behaviour, allowing for adaptive decision making in resource-constrained environments. Real-time visualization and data logging in the cloud are supported by the Blynk platform and Google Sheets. The results of experiments show that it is possible to achieve a capture efficiency higher than 90%, with an adaptive energy consumption ranging from 3 W in conditions of low emission to 11 W in the maximum emission conditions of $CO_2$. The coefficient of determination $R^2$ is 0.93, which is an indication of the reliability of the emission short-term prediction. The system is a prototype that demonstrates the potential of an adaptive, IoT-enabled carbon capture system and provides a scalable basis for its industrial adoption.

**Keywords:** NumPy; Carbon Capture; IoT; Capture Rate; Real-Time Monitoring; Emission Trends; Industrial Revolution

## 1. Introduction

The recent decades have shown an unprecedented rate of $CO_2$ concentration in the atmosphere caused mainly due to the burning of fossil fuels, industrial performance, and power stations. Traditional methods of carbon capture, although effective in theory, tend to be weak in flexibility, energy use, and real time feedback. Such limitations limit their sensitivity to changing levels of emissions and inefficiencies of operation. Recent developments in IoT-based sensing and automation offer the solution to these problems by offering the ability to monitor continuously, control adaptively, and make decisions based on data. With the incorporation of sensors, embedded computing platforms, and cloud-based dashboards, carbon capture systems will transform the inert infrastructures to self-regulating and intelligent frameworks. This paper is based on this fact and suggests an IoT-based post-combustion carbon capture system that will be able to track emissions, adjust the rates of capture and forecast the tendencies in real-time.

Excess carbon dioxide simulates global warming, causing many environmental threats, including animal adaptations, plant production, and natural disasters, and also affecting human health. This all started in 1750 after the Industrial Revolution, and today the $CO_2$ emissions have increased by more than 50%, and by November 2024 the normal range of $CO_2$ will have become 424.31 ppm. One of the major factors that is contributing to this increase is burning fossil fuels from human and industrial activities [1]. At this point in time, planting endless yards of trees is not enough to reverse the damage done; however, in 1972, the first carbon capture system was installed, storing 200 million tons of $CO_2$ in the United States [2]. There are three different types of capture technologies: pre-combustion, where the carbon monoxide is converted to carbon dioxide and removed due to the process of gasification, where hydrogen and carbon monoxide are produced from synthesis gas; oxy-combustion, where $CO_2$ is captured from burning coal in an oxygen-intense environment; and the technology used in this project, post-combustion, where $CO_2$ is captured by gathering flue gases emitted from burning fossil fuels and then separating it from the other gases [3].

By far, carbon capture technology is the most effective way to neutralize carbon emissions, where $CO_2$ is absorbed, separated, compressed, and transported to underground reservoirs [4–6]. With constant technological developments, combining IoT applications with carbon capture systems can increase the efficiency of the system by real-time monitoring of capture rates and parameters and having an adaptable system that is energy effective [7,8]. This will be implemented by using different sensors to collect data on parameters like $CO_2$ levels, flow, pressure, and energy. The collected data is communicated to a Raspberry Pi, which transmits PWM signals to control the absorption rate and executes logic and calculations that are displayed via a monitoring dashboard. This system is applicable to be used in power plants and industries that have high $CO_2$ emission rates. Overall, this project promotes a balanced and sustainable ecosystem holding technical and environmental significance.

In contrast to traditional, post-combustion carbon capture systems, which work at fixed capture rates and with offline feedback, the proposed system proposes an IoT-based closed-loop system that continuously varies capture rates according to real-time $CO_2$ sensing [9–11]. The adaptive PWM-based actuation, embedded intelligence and cloud-based monitoring allow this work to be responsive, consume less energy, and predictive in emission control, unlike the previous work, which was static or focused on monitoring [12,13].

Whereas the industrial carbon capture systems are based on chemical absorption, adsorption and separation using membrane technology, the prototype in this paper is centered on control, monitoring and adaptive regulation layer of the said systems [14]. The existing implementation exhibits the managed gas intake, concentration minimization at the input, and the energy-conscious work with the help of IoT technologies [15]. Chemical separation and long-term $CO_2$ storage are also considered extensions of the proposed framework as opposed to the features of the current prototype.

### 1.1. Background

The recent innovations in embedded sensing, low-power computing, and cloud-connected IoT systems have made it possible to transform the previously static industrial systems into intelligent adaptive infrastructures [16]. When applied to carbon capture, this type of technologies enables continuous monitoring of emissions, closed-loop regulation of capture rates, and optimization of energy use based on data [17]. Most available carbon capture systems are however fixed rate capture systems with offline monitoring and do not have predictive ability [18,19]. This paper fills such gaps by postulating a carbon capture framework based on the Internet of Things that entails real-time sensing, adaptive PWM-based actuation, and lightweight predictive analytics. In contrast to the traditional carbon capture systems that have constant capture rates, the proposed system allows adaptive control based on PWM that is controlled by real-time sensing and internal prediction, thus facilitating energy-efficient and proactive mitigation of emissions [20].

### 1.2. Previous Works

Recent progress in artificial intelligence (AI), machine learning (ML), and intelligent communication systems has had a major impact on the evolution of smart infrastructure such as power distribution networks, unmanned aerial vehicle (UAV) systems, and integrated sensing and communication platforms [21,22]. All these technologies are evidence of how data oriented intelligence and real-time communication can foster the efficiency of monitoring, safety and the flexibility of the system [23,24].

Tian et al. (2025) came up with an autonomous drone-based, dynamic identification system, which is based upon AI to identify hazards within power distribution networks. The project combines the inspection of equipment with the abilities of drones and the use of AI in analyzing images and identifying their defects and possible safety risks. The methodology enhances the process of inspection by using aerial data collection and smart analysis to minimize human risk. The system facilitates the early warning systems that enable early intervention of distribution channels. Whereas certain quantitative values are not widely documented, the practical implementation outcomes indicate the increased safety and operational efficiency, which proves the feasibility of AI-powered autonomous inspection systems in the power system [25,26].

The article by Baig and Shahzad (2022) examined the application of machine learning and artificial intelligence in enhancing the performance of UAV communication and networking. The paper identifies the importance of ML as one subgroup of AI in dealing with issues related to dynamic, mobile, and IoT-based environments. Enhanced UAVs with intelligence that is supported by ML were demonstrated to be more dependable when used in the life threatening concerns like rescue, surveillance, and emergency response. The study determines the gaps in the current strategies of UAV communication and the necessity of adaptive learning models to attain greater consistency and strength of transmission. The results indicate that the incorporation of ML and AI can be of great help to optimize the efficiency of UAVs in the fast-changing communication environment [27].

Temiz et al. (2025) conducted an in-depth review of the deep learning-based solution to the integrated sensing and communication (ISAC) system, especially focusing on the 6G networks. The authors classified the state-of-the-art deep learning methods implemented on ISAC tasks namelywaveform design, channel estimation and interference mitigation. The review notes that the deep learning methods have the capability of providing near optimal solutions with fewer computational complexities than the traditional optimization approaches. Also integration of sensing and communication into one platform proved to be less complex in terms of hardware and also more efficient in terms of energy consumption. Although these benefits are found, the study also reveals challenges of integration of system, data dependence, and real-time deployment [28].

Hashesh et al. (2022) introduced a general overview of AI-based UAV communication systems, including the importance of the system in future wireless networks. The paper explains such advanced machine learning approaches as multi-armed bandits, federated learning, and meta-learning as effective in improving the performance of UAV networks. These artificial intelligence-based solutions allow flexible resource distribution, autonomous learning, and scalability in UAV communications. Although the investigation is mainly based on the conceptual frameworks and the future research issues, it puts a solid background to AI-assisted UAV networking and indicates the areas of research which should be critical to ensure an actual deployment [29].

Bush (2014) discussed the use of machine intelligence in the smart grids and the significance of communication and networking infrastructures in facilitating the intelligent power systems. The chapter covers classical optimization techniques including linear and nonlinear programming, dynamic programming and Lagrangian techniques and machine learning techniques including neural networks and particle swarm optimization. The concept of cognitive radio and cognitive networking technologies is introduced as some of the enablers of adaptive communication in smart grids. The paper highlights that proper communication architectures are critical towards supporting distributed intelligence and advanced control strategies in contemporary power grids [30].

Taken together, these works prove the fact that smart sensing solutions, AI-based data processing, and efficient communication systems are the key preconditions of smart systems of the next generation. Although extensive literature on AI has been done in the areas of power grids, UAV communications and integrated sensing, little research has been done on the application of lightweight predictive analytics and IoT-based adaptive control to carbon capture systems. The current work can fill this gap by combining real-time sensing, adaptive PWM-based actuation, and low-complexity emission prediction into an IoT-enabling carbon capture framework and makes the concepts of intelligent communication and automation relevant to the sphere of environmental sustainability.

The current research on AI-driven communication and sensing systems proves the validity of smart data-based structures in infrastructures. As an illustration, AI-powered defense systems in power distribution systems allow fault detection in time and resilience [26]. Likewise, the topic of sensing and communication coverage in Internet of Drone Things (IoDT) is also being addressed, and the necessity to be adaptive and able to acquire data in real-time and network intelligence is emphasized [27]. The concept of feature encoding via deep neural network has been investigated in the context of automated health monitoring compared to online communication systems, and it focuses on scalable sensing and cloud analytics [28]. Although the studies deal with power systems, UAV networks, and healthcare, its main concepts intelligent sensing, adaptive control, and efficiency in communication can be directly applied to smart environmental systems. Nonetheless, there is a scarcity of literature on the implementation of lightweight predictive analytics and IoT-based closed-loop control to carbon capture systems, which justifies the current research.

## 2. Project Objectives

The main purpose of this project is to implement a system that can identify carbon emissions from industrial practices and power plants through post-combustion carbon capture and combining IoT for system automation and real-time data monitoring and analysis. This is achieved through the following objectives:

- Detect different levels of $CO_2$ from the atmosphere via gas sensor;
- Calculate the amount of $CO_2$ stored in the storage tank by the change in pressure;
- Assure that the system consumes a minimum amount of energy by monitoring the energy consumption through voltage and current sensors;
- Integrate a linear regression model using NumPy's polyfit function to predict regression-based trend estimation can support adaptive control decisions in resource-constrained IoT systems for $CO_2$ emissions;
- Manipulate the system to adjust absorption rates using pulse width modulated signals based on the levels of $CO_2$ detected to reach more than 90% capture relative efficiency;
- Hazardous levels of $CO_2$ trigger a buzzer as an alarm system;
- Google Sheets and the Blynk platform are used for real-time data storing and monitoring.

## 3. Project Applications

The Smart IoT-Based Adaptive Carbon Capture Control Framework is used as an advanced technique to monitor and neutralize emissions as well as being a profitable asset in the oil and gas industries. The carbon capture system can be deployed in cement and steel production industries, power plants that operate by burning fossil fuels, and oil and gas production industries to capture the $CO_2$ and neutralized emissions and store it in underground reservoirs. Additionally, the stored $CO_2$ can be recycled and used in the oil and gas industries in enhancing oil and coalbed methane recovery, which increases the production of oil and natural gas and becomes a profitable asset within the industry.

The linear regression model being developed on the basis of polyfit function of NumPy is only applied in estimating the short-horizon trends through consideration of recent sensor data. Training and testing of the model were done on the same data and the model was not cross-validated or independently tested. Therefore, the goodness-of-fit and not the generalization ability are captured in the reported $R^2$ value. The data of gas sensors are chronological and time-sensitive. Certain potentially important factors were not explicitly modelled in this prototype, including autocorrelation, drift and non-stationarity. Sophisticated time-series models (e.g., ARIMA, Kalman filters, or LSTM-based models) are out of the scope of this work and are listed as future research directions.

## 4. Applied Methodology

The Smart IoT-Based Adaptive Carbon Capture Control Framework uses many sensors to detect different parameters, Raspberry Pi for automation, logic execution, and calculations, and both Google Sheets and the Blynk dashboard for real-time monitoring. The system aims to monitor current emissions, predict future emissions, and optimize absorption rate by controlling the vacuum air pump absorption rate. The project took 8 months to be executed, as it was planned in 4 months and implemented in the other 4 following An Agile approach was adopted, developing the system in short iterative sprints with early testing of individual hardware and software components, followed by full system integration and deployment using Google Sheets and the Blynk platform. The whole system was tested via test points and cases, assuring that the objectives set for the project were achieved in different environments and stages. Safety measures were taken the whole time, and ethical aspects were considered. Measured sensor data and simulated variables were used for different purposes in the system. Sensor readings were employed for real-time monitoring and control triggering, while simulated pressure and flow values were included only for conceptual demonstration and system visualization. These datasets were not combined for experimental validation or quantitative performance evaluation.

## 5. System Design

### 5.1. Block Diagram

The system architecture can be functionally divided into four interconnected layers:

(i) Sensor Layer.
(ii) Controller Layer (Raspberry Pi Zero 2W with MCP3008 ADC).
(iii) Control and Prediction Layer (PWM-based pump control and regression-based emission prediction).
(iv) Cloud and Visualization Layer (Google Sheets and Blynk dashboard).

This layered approach enables modular analysis and facilitates scalability and reproducibility.

The proposed architecture of a Smart IoT-Based Adaptive Carbon Capture Control Framework is shown in **Figure 1**, focusing on the innovative combination of the IoT-based sensing, adaptive PWM control, and predictive analytics. The system, in contrast to classical carbon capture arrangements, introduces a closed-loop control system in which real-time measurements of $CO_2$ dynamically control the rate of absorption, and such a system is supported by emission prediction logic to achieve proactive response of the system. The single-data pipeline facilitates the real-time control, observation, prediction, and visualization on the cloud. The inputs of the system consist of 5 different sensors, including the MH-Z19B gas sensor that was used to detect the different levels of $CO_2$, voltage and current sensors to monitor the energy consumed by the vacuum air pump, a flow sensor to ensure gas flow and system effectivity, and a pressure sensor in the storage tank that is used to calculate the amount of gas stored using the ideal gas law. And an ADC is used to convert analog signals to digital and transmit them to the Raspberry Pi, which is the brains of the system. From the raspberry, PWM signals are sent to the DC motor driver depending on the levels of $CO_2$ gas that have been detected, which controls the speed of the vacuum air pump absorption rate, where the $CO_2$ is then transported to a storage tank. Also, the data detected from the gas sensor is stored and added to a linear regression model to predict future readings, and logic is sent to a buzzer on whether the $CO_2$ levels are high or low as an alarm system. Simultaneously, all the data are sent every few seconds to Google Sheets with date and time stamps, including all the parameters and outputs, and the data are also sent to the Blynk dashboard for real-time monitoring. Key innovations highlighted in **Figure 1** include:

- Closed-loop PWM-based adaptive capture control driven by real-time $CO_2$ sensing.
- Integration of predictive emission modeling within the embedded controller.
- Unified data pipeline enabling simultaneous control, prediction, and cloud visualization.
- Energy-aware operation through adaptive duty-cycle modulation.

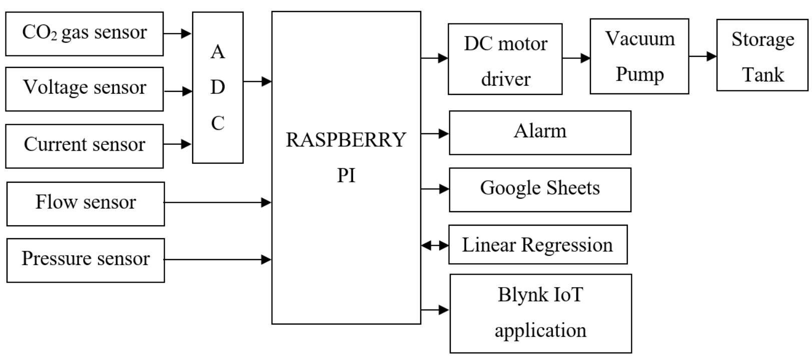



**Figure 1.** System Block Diagram.

### 5.2. Flow Chart

The system starts by detecting the levels of $CO_2$ in the atmosphere, and then the voltage, current, pressure, and flow parameters start to collect data and send it to the Raspberry Pi. The threshold for normal $CO_2$ levels is set to

400 ppm, where if the readings are 400 ppm or less, then the signals sent to the motor driver have a 30% or less duty cycle, where the vacuum air pump is programmed not to work to save energy due to it being within the normal range. However, when the ppm reaches above 420, the vacuum air pump starts to work as the duty cycle starts to increase from 30% and stops at 50%, corresponding to 2,500 ppm. When the $CO_2$ levels are above 2,500 ppm, then the buzzer is triggered and the vacuum air pump speed increases due to PWM signals having more than 50% duty cycles. Based on that, the efficiency of the capture is found, the amount of gas stored is calculated, and predictions are made, with all these outcomes stored in Google Sheets and sent to the Blynk monitoring dashboard. This loop repeats every second as shown in **Figure 2**. Sensor data are acquired at a frequency of 1 Hz. Analog sensors (MH-Z19B gas sensor, voltage sensor, current sensor) communicate with the Raspberry Pi via the MCP3008 ADC using the SPI protocol, while digital sensors such as the flow sensor and pressure sensor interface directly through GPIO pins. PWM signals for motor control are generated at a frequency of 1 kHz via GPIO18. Sensor data are acquired at 1 Hz. Analog sensors interface via MCP3008 ADC using SPI, while digital sensors communicate via GPIO. PWM signals are generated at 1 kHz.

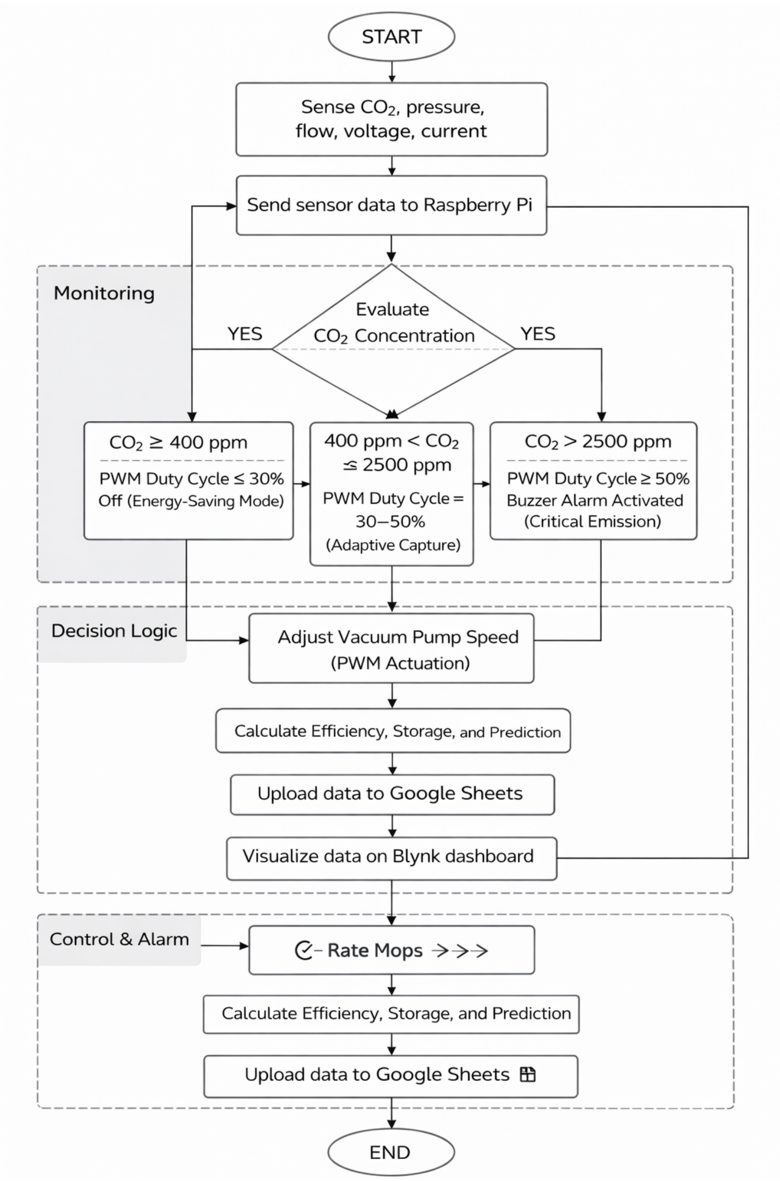



**Figure 2.** Simplified system flowchart showing separated monitoring and control processes with threshold-based decision logic at 400 ppm, 420 ppm, and 2,500 ppm.

The $CO_2$-based control logic follows a hierarchical threshold model in which emission levels are evaluated once per cycle and mapped to predefined actuation states, enabling stable and energy-efficient operation while maintaining safety.

## 5.3. Design Equations

To ensure the systems effectiveness and reliance, the theoretical aspect of the system design should be discussed where input and output relationships are stated, mathematical equations are stated and proven to match with test results to minimize error. MH-Z19B sensor was calibrated by calculating the base resistance (Ro) under clean air, after a 24 h preheating period, according to the manufacturer suggestions. The flow sensor calibration was done by utilizing the conversion factor of 330 pulses per liter as specified by the manufacturer with the pressure sensor output being mapped linearly by the use of known voltage-to-pressure reference points. The calibration consistency was also confirmed by repeating measurements under controlled conditions although industrial reference instruments were not at hand. The gas mass estimation using the ideal gas law assumes constant temperature (298.15 K), a sealed chamber, and negligible leakage. Deviations from these assumptions, particularly due to the unpressurized prototype container, introduce uncertainty in absolute mass estimation; therefore, calculated values represent approximate upper bounds rather than exact measurements. The duty cycle–$CO_2$ relationship was derived empirically through repeated testing. Minor deviations (±5%) were observed due to sensor noise and environmental variability. Despite this, the monotonic relationship between $CO_2$ concentration and duty cycle confirms reliable adaptive behavior suitable for real-time control.

In the Smart IoT-Based Adaptive Carbon Capture Control Framework all the data obtained, functions, automation and outputs are based on the amounts of $CO_2$ detected, therefore the MH-Z19B gas sensor accuracy is proportional to the systems functionality as shown in **Figure 3**. This is verified by testing that the $R_S/Ro$ ratio of the sensor is 1 in clean air where $R_S$ is found using

$$R_S = R_L \times (V_{cc} - V_{out}/V_{out}) \tag{1}$$

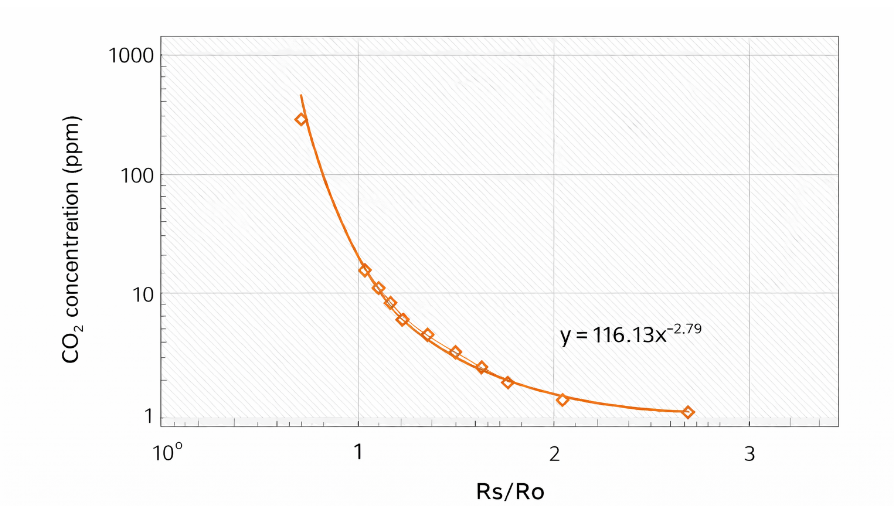



**Figure 3.** MH-Z19B sensitivity curve for $CO_2$ showing $R_S/Ro$ versus $CO_2$ concentration (ppm) on a logarithmic scale, based on manufacturer calibration data.

And then the $R_S/Ro$ ratio is found where Ro value is set by the sensor resistivity graph as baseline value in clean air, where when the $R_S/Ro$ value is more than 1 then the amount of $CO_2$ present is more than calibrated clean air value. In this project, the Ro value was calibrated to give a constant of 8,320 [7], where $R_L$ = 10 K ohms, $V_{cc}$ = 5 V of supply voltage and assuming that $V_{out}$ = 2.7 V then,

$$R_S = 10K \times (5 - 2.7/2.7) = 8,518.51ohms$$

Therefore,

$$R_S/Ro = 8,518.5/8,320 = 1.02$$

And from the $R_S/Ro$ ratio the ppm of $CO_2$ can be found based on the MH-Z19B sensitivity equation for $CO_2$.

Given,

$$y = 116.13 \times x^{(-2.79)} \tag{2}$$

which can be used to find ppm of $CO_2$ using,

$$ppm = a \times (R_S/Ro)^b \tag{3}$$

where a = 116.13 and b = −2.79 [9].

Therefore, we can implement this by assuming that $R_S/Ro$ value is 0.6, then

$$ppm = 116.13 \times 0.6^{(-2.79)} = 482.95ppm$$

Also, another sensor parameter is pressure, since the pressure sensor gives out voltage output, the system uses linear interpolation to convert the voltage output to pressure in kPa.

Linear interpolation formula

$$(y) = y1 + (x - x1)(y2 - y1/x2 - x1) \tag{4}$$

When replacing it with sensor voltage output and minimum pressure is zero then.

After finding the pressure, the result is used to find the amount of gas stored in the storage tank by using the ideal gas law, where the tank volume is = 1,330.166 $cm^3$, temperature used is 298.15 K. After finding the amount of gas, the result is multiplied by the molar mass of $CO_2$ (44 g/mol)

$$PV = nRT \tag{5}$$

Where rearranged is,

$$\text{Mass of gas stored(g)} = (PV/RT) \times 44 \tag{6}$$

The ideal gas law is utilized in this work as a pure modeling, in theory only, to estimate the behavior of the relative system in idealized conditions. The calculated mass of the gas is not a mass of physically stored $CO_2$ since the prototype container is not a sealed and pressure-rated container. Based on this, all the mass values of the gas are considered as simulated measures that would be used to check the control logic, as opposed to experimental measures. According to the tank volume, and assuming that the pressure does not exceed 1–1.2 atm because the used storage in the prototype is a plastic jar and avoiding jar explosion due to overpressure the pressure should not exceed 1–1.2 atm. If so, then the gas needs to be released. Therefore,

$$\text{Max Mass} = (1 \times 1,330.166/0.0821 \times 298.15) \times 44 = 2,391\text{g of } CO_2 \tag{7}$$

The flow sensor works by falling edge detection where 1 signal pulse is counted at every signal drop from high to low. The sensor is calibrated to represent 330 pulses per liter of flow therefore to find the flow rate in L/min,

$$\text{Flow Rate} = \text{pulse(1s)/pulse per liter} \times 60 \tag{8}$$

When it comes to the vacuum pump automation, the system is designed to give a signal with 100% duty cycle at 5,000 ppm of $CO_2$ detected. Based on this scaling, at 2,500 ppm the duty cycle reaches 50%, and at that time the buzzer is triggered and alarm signals are activated.

$$\text{Duty Cycle(\%)} = (\text{Ton/Ton + Toff}) \times 100 \tag{9}$$

This value is set based on **Table 1**.

**Table 1.** $CO_2$ levels impact.

| $CO_2$ Levels | Condition |
|---|---|
| 400 ppm | Normal outdoor air level |
| 400–1,000 ppm | Normal indoor level |
| 1,000–2,000 ppm | Poor air quality |
| 2,500–5,000 ppm | Headaches, heartrate increase, nausea, loss of focus and fatigue |
| 5,000–50,000 ppm | Toxication due to loss of oxygen |
| 50,000–100,000 ppm or more | Coma and possibility of death |

The systems overall efficiency is measured using:

$$\text{Efficiency } \% = 1 - (\text{CO}_2 \text{ detected before the capture})/(\text{CO}_2 \text{ detected after the capture}) \times 100 \tag{10}$$

For energy consumption, the system monitors the energy consumed by the vacuum air pump when it is absorbing different levels of $CO_2$ by measuring instantaneous power, therefore the faster the capture is then the more power is consumed. So, assuming that the voltage and current sensors give readings of 12 V and 2.5 A, then the instantaneous power is

$$P = VI = 12 \times 1.5 = 18W \tag{11}$$

To ensure that the system is energy effective and does not counteract the overall impact, the vacuum air pump works at a duty cycle of 30% where the $CO_2$ are considered safe so that energy is saved.

## 6. Schematic Connection

The hardware component connections are shown using Proteus 8 through a schematic connection. As shown in **Figure 4**, all the $CO_2$ sensors, current sensors, and voltage sensors are connected to an ADC, which is connected to a Raspberry Pi Zero 2W. The sensors are represented by potentiometers, the voltage sensor is represented by a voltage divider, and a 5 V battery represents the VCC and GRND pins in the Raspberry Pi Zero 2 due to component unavailability. The connection to and from the ADC, indicated in red in **Figure 4**, shows that the analog output of the MQ-125 sensor is connected to CH0 of the MCP3008. The ACS712 current and the voltage sensors, the ground, and the VCC pins are connected to a 12 V supply of the driver, and the output pin is connected to CH1 and CH2 of the MCP3008.

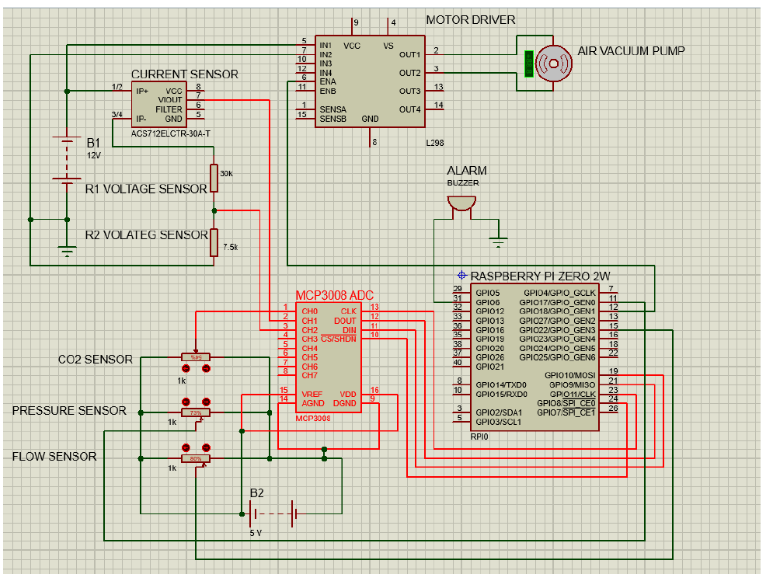



**Figure 4.** MCP3008 ADC schematic connections.

The ADC itself is connected to the Raspberry Pi by connecting VDD, VREF, AGND, and DGND to the GND and 5 V pins of the Raspberry Pi. As for the SPI communicating pins, CLK is connected to GPIO11 to synchronize data bits, DOUT is to GPIO9 (MISO), where the digital outputs of the ADC are sent to the Raspberry Pi, and DIN is to GPIO10 (MOSI), where the Raspberry Pi gives instructions to the ADC, and finally the CS/SHDN is connected to the GPIO8 so that the ADC starts and stops communicating depending on if the Raspberry Pi has set the chip select pin to high or low.

The other components, including the pressure sensor, flow sensor, motor driver, and buzzer, are connected directly to the Raspberry Pi through GPIO pins as shown in **Figure 5**. The pressure sensor is connected to GPIO17, the flow sensor to GPIO22, the buzzer to GPIO6, and the monitor driver specifically to GPIO18 for PWM signal control as shown in **Figure 6**.

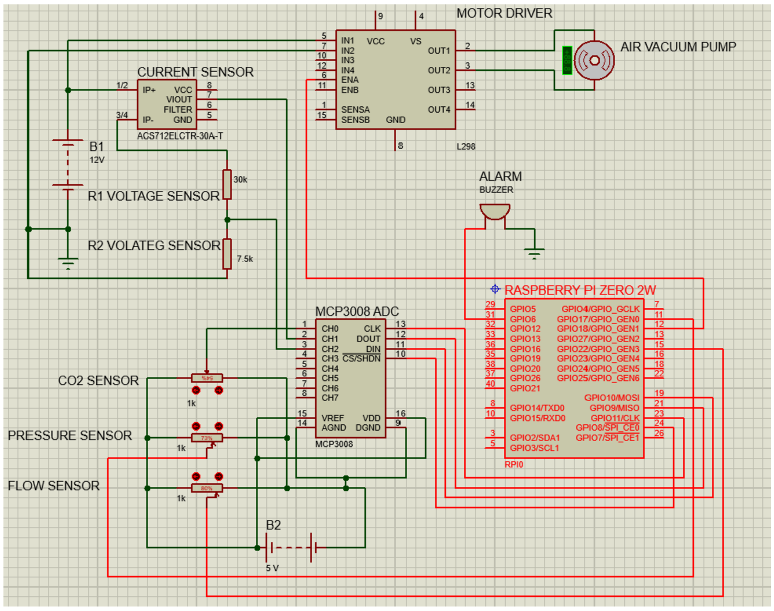



**Figure 5.** Raspberry Pi schematic connections.

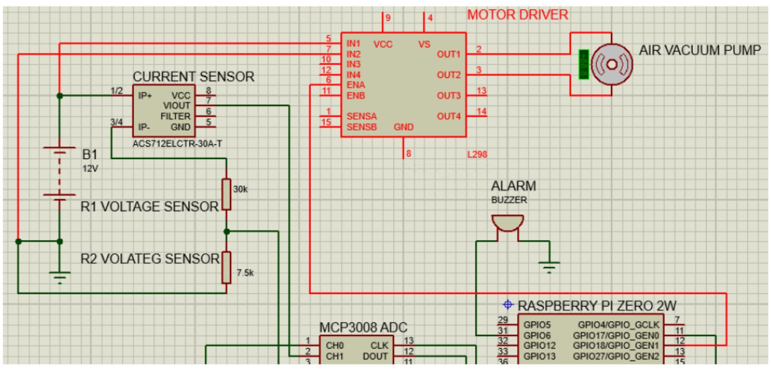


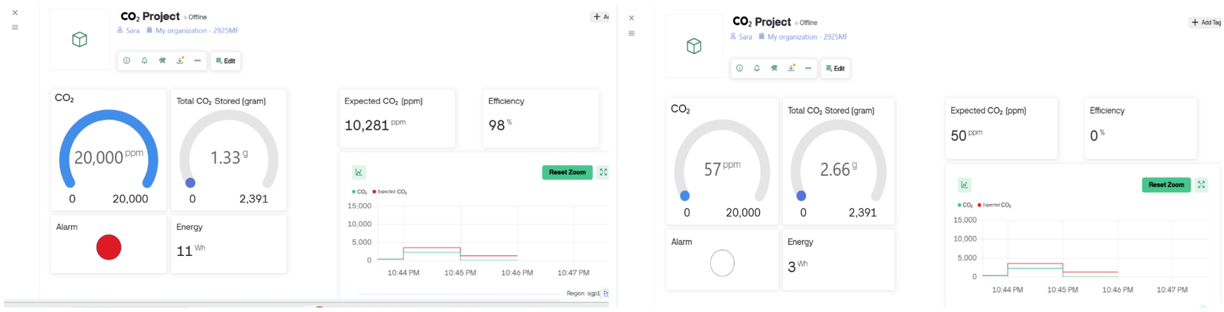

**Figure 6.** Raspberry Pi schematic connections.

The GPIO18 from the Raspberry Pi is connected to the L298N motor driver through the enable A pin (ENA), and IN1 and IN2 are connected to 12 V and ground of an external power supply, while OUT1 and OUT2 are connected to both sides of the vacuum air pump to control the motor speed.

## 7. Results

These figures are illustrative dashboard screenshots intended to demonstrate the user interface and data flow. They are not presented as scientific plots and do not include statistical analysis, uncertainty bounds, or calibrated axes. In **Figure 7a**, the Blynk dashboard shows the alarm being on due to a very high $CO_2$ emission that is detected; the energy consumed by the vacuum air pump is 11 W due to the speed being at maximum potential, and the capture relative efficiency has reached 98%. However, opposing that, **Figure 7b** shows a $CO_2$ detection level that is below normal ranges, and due to that, the alarm is off, the efficiency is 0, and the energy consumed is at 3 W due to the vacuum air pump not working and no capture occurring.

When it comes to predicting future emissions as shown in **Figure 8**, a prediction value is presented and also a graph showing the difference between the actual and predicted value and how the emission rates are changing over time. The prediction value is shown every minute where the prediction at 2:40:00 was relatively high based on the emission detected at 2:39:00 and since the detection was lower than expected, the systems prediction of the amount of $CO_2$ detected has decreased. Regardless of the differences, the system detects the emission trends and gives value based on that.




(**a**) (**b**)

**Figure 7.** (**a**) Blynk dashboard at high $CO_2$ emission. (**b**) Blynk dashboard at low $CO_2$ emission.

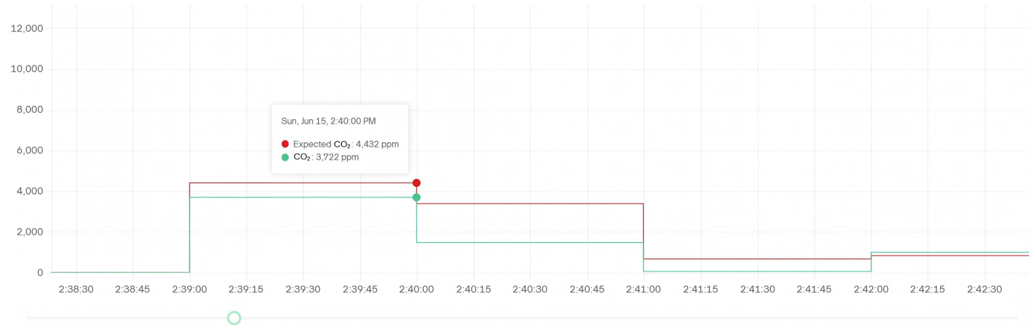
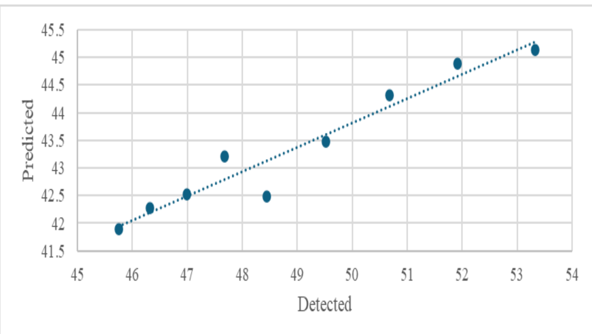



**Figure 8.** $CO_2$ detected vs. Predicted.

The accuracy of the predictions was tested using detected $CO_2$ levels and corresponding predictions, plotted into a graph where the $R^2$ coefficient was found to be 0.93. These results are presented in the form of illustrations such as tabular results and graph below in **Figure 9**.

| Time | CO₂_ppm | CO₂_predicted |
|---|---|---|
| 2025-06-16 12:23:06 | 45.13916867 | 53.32 |
| 2025-06-16 12:23:12 | 44.88668062 | 51.91 |
| 2025-06-16 12:23:18 | 44.3174955 | 50.67 |
| 2025-06-16 12:23:23 | 43.47205323 | 49.52 |
| 2025-06-16 12:23:37 | 42.48752206 | 48.44 |
| 2025-06-16 12:23:46 | 43.20483263 | 47.68 |
| 2025-06-16 12:23:52 | 42.51561687 | 46.99 |
| 2025-06-16 12:23:58 | 42.27738342 | 46.32 |
| 2025-06-16 12:24:03 | 41.88781394 | 45.75 |




(**a**) (**b**)

**Figure 9.** (**a**) Detected $CO_2$ levels and corresponding predictions; (**b**) Graphical representation of detected $CO_2$ levels and corresponding predictions.

The linear scaling of duty cycle from 0–100% over a 0–5,000 ppm range was selected to align with established $CO_2$ exposure thresholds. $CO_2$ levels were measured using the MH-Z19B sensor, with relative ppm changes validated through controlled exposure to butane gas as a proxy, recognizing the sensor's cross-sensitivity limitations. The signals controlling the rate at which the $CO_2$ is getting absorbed are transmitted from the Raspberry Pi to the motor driver, where the higher the $CO_2$ level is the longer the duty cycle is. **Figure 10** showcases the PWM signals vs. Emission levels.

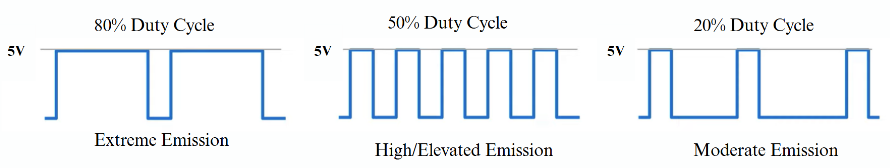



**Figure 10.** PWM signals vs. Emission levels.

This was testing by measuring the duty cycle at different $CO_2$ levels detected, providing us with results shown in **Table 2**, and due to these results and the **Table 1** the system is programed to turn the vacuum air pump at a duty cycle of 30% since $CO_2$ levels up to 2,000 ppm are considered safe regardless of the low air quality, which also allows the system to be energy effective.

**Table 2.** PWM signals duty cycle corresponding to $CO_2$ levels test results.

| $CO_2$ Levels Detected | Duty Cycle |
|---|---|
| 290 ppm | 4% |
| 769 ppm | 15% |
| 1,600 ppm | 32% |
| 3,298 ppm | 65% |
| 4,729 ppm | 95% |

Therefore, the detected levels of $CO_2$ concentration were linearly scaled to the corresponding PWM duty cycle levels as shown in **Table 2**. The PWM duty cycle linearly ranged with a change in $CO_2$ concentration between 290 ppm and 4,729 ppm, such that 4,729 ppm was operated at a 95% duty cycle, allowing a linear and direct relationship to be drawn between the gas concentration and the system output. $CO_2$ was measured and the results were automatically recorded and saved in Google Sheets to enable real-time monitoring, data analysis and storage of the recorded results. The data collected and outputs obtained are all stored in Google Sheets so that they can be used as reference if needed with date and time stamps, the dataset updates each few seconds as long as the system is working. The Google Sheet Dataset related details are displayed in **Figure 11**. As well as a real-time pictorial representation of the Smart carbon capture prototype is displayed in **Figure 12**.

| | A | B | C | D | E | F | G | H | I |
|---|---|---|---|---|---|---|---|---|---|
| | Table1 | | | | | | | | |
| 1 | Time | co2_ppm | co2_after_capture | flow_rate | volume | pump_speed | energy | co2_predicted | efficiency |
| 1854 | 2025-06-18 19:51:44 | 1387.833522 | 115.1934843 | 0 | 1.328 | 0 | 3.446222656 | 1165.41 | 97.63 |
| 1855 | 2025-06-18 19:51:52 | 277.319819 | 115.1934843 | 0 | 1.328 | 0 | 3.439774902 | 1141.35 | 97.63 |
| 1856 | 2025-06-18 19:51:58 | 485.0828626 | 115.1934843 | 0 | 1.328 | 0 | 3.43034082 | 1184.28 | 97.63 |
| 1857 | 2025-06-18 19:52:04 | 2072.316476 | 115.1934843 | 0 | 1.328 | 0 | 3.435770508 | 1596.43 | 97.63 |
| 1858 | 2025-06-18 19:52:11 | 38167.51243 | 115.1934843 | 0 | 1.328 | 60 | 11.65309577 | 10281.5 | 97.63 |
| 1859 | 2025-06-18 19:52:20 | 142.2243293 | 142.2243293 | 3.272727273 | 1.992 | 30 | 6.29867033 | 4898.01 | 98.3 |

**Figure 11.** Google Sheets Dataset.

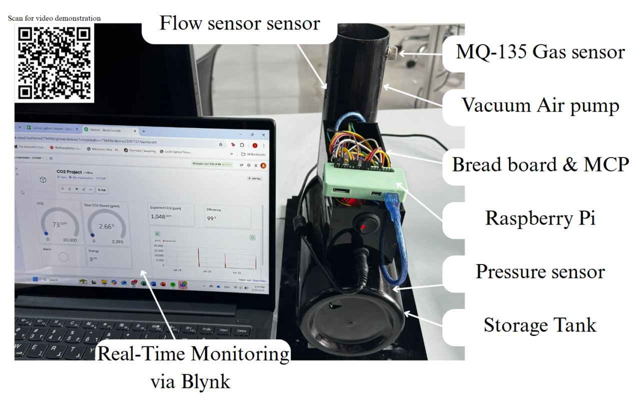



**Figure 12.** Smart carbon capture prototype.

Although the ideal gas law is used to estimate stored $CO_2$, the prototype container is neither sealed nor pressurized. Hence, the calculated $CO_2$ mass values represent theoretical approximations rather than experimentally measured quantities. These estimates are based on ideal assumptions and serve as upper-bound indicators of system behavior. Accordingly, all reported $CO_2$ mass values should be interpreted as simulated quantities used for system validation. Future work will incorporate sealed, pressure-rated vessels and industrial-grade sensors for accurate mass quantification. **Table 3** showcases Parameters, Value/Range, and Notes/Remarks.

**Table 3.** PWM signals duty cycle corresponding to $CO_2$ levels test results Cumulative Energy Analysis of the Smart Carbon Capture System.

| Parameter | Value/Range | Notes/Remarks |
|---|---|---|
| Instantaneous Power | 3–11 W | Measured during adaptive vacuum pump operation at varying $CO_2$ levels |
| Duty Cycle | 0–100% | PWM control proportional to detected $CO_2$ concentration |
| Average Duty Cycle | 50% | Estimated based on $CO_2$ levels over typical operation |
| Cumulative Energy (6 h operation) | 33 Wh | (E = P\times t\times\text{Duty Cycle} = 11\times 6\times 0.5) |
| Cumulative Energy (24 h extrapolated) | 132 Wh/day | Linear extrapolation assuming similar $CO_2$ emission patterns |
| Energy per unit of adaptive operation (Wh) | 13.8 Wh | $CO_2$ captured |
| Measurement Interval | 3–5 s | Sensor readings and control signals logged at this interval |

The energy analysis is reported in terms of power consumption of a system and dependent of the duty-cycle. Measures based on theoretical values of $CO_2$ mass have been eliminated in order to prevent misleading comparison with industrial carbon capture technologies. The performance of the system at experiments shows that it is able to achieve a dynamically reduced inlet gas concentration by operating the adaptive actuation. Although the process of capturing the gas and temporary trapping is referred to as capture, there is no chemical separation and storage of the gas in the present prototype. Thus, the findings confirm adaptive gas handling and control performance, and not the long-term performance of carbon sequestration.

## 8. System Validation

During the implementation of the project and finalizing it, the system has been tested at every stage and under different conditions to ensure that the system meets its main output requirements. These requirements include the system's ability to detect and respond to different levels of $CO_2$ and having the absorption rate adapt to those changes by having PWM signals controlling the vacuum pump speed. Alternatively, the system triggers an alarm system in case the $CO_2$ levels reach above the set threshold, and all of the data detected, including future emission predictions, are monitored in real time via the Blynk dashboard and are recorded simultaneously in Google Sheets with timestamps for records.

These outputs were verified through different tests. Firstly, validating the system's ability to detect different levels of emissions, where butane gas from a lighter was exposed to the MH-Z19B gas sensor at different levels and distances, and based on that, the gauge in the Blynk dashboard was monitored for changes in gas exposure levels, and ensuring that whenever the detection value reaches 2,500 ppm or more, the buzzer works and the alarm is on in the monitoring dashboard. Secondly, the absorption rate adaptation was tested in 2 different ways: by simulating PWM signals duty cycles via code at different $CO_2$ levels detected for precise testing and by observing the vacuum pump work faster and make more noise the more gas is exposed, validating the vacuum's adaptation. Also, the $CO_2$ prediction levels were verified by analyzing the graphs provided in the Blynk monitoring dashboard, where the system's ability to follow emission trends was verified, and finding an $R^2$ value of 0.9, proving the accuracy of the predictions. Finally, the pressure and flow, regardless of the inaccurate readings due to constraints, ensured that the readings and data logged were realistic and reliable, where the flow rate and the stored gas increase proportionally to the increases of $CO_2$ that are detected.

The MH-Z19B gas sensor that was used in this research has cross-sensitivity to other gases such as NH3, benzene, smoke and hydrocarbons; thus, the values obtained of the $CO_2$ are viewed as relative or proxy-based readings as opposed to actual concentrations. The sensor was used to test the system in terms of its capability to monitor small changes in the gas levels, adjust the capture rate using PWM-controlled actuation, and react dynamically to the changes in emissions. Calibration was done repeatedly under controlled conditions and as a result relative concentration changes with time were able to be tracked. Even though the butane gas was used as a proxy in the experiments, the measured monotonic dependence between sensor response, duty cycle adjustment and capture relative efficiency proves the legitimacy of the control strategy. The exact measurement of $CO_2$ is not within the capabilities of the prototype, and future research will also introduce $CO_2$-sensitive sensors to increase the accuracy of measurements and their applicability in the industry.

## 9. Critical Evaluation

The suggested Smart IoT-Based Adaptive Carbon Capture Control Framework was tested in several test periods lasting about 6 h in operation. The sampling rate of sensor data was 3–5 s, and approximately 5,000 sensor data samples were obtained, which comprised $CO_2$ concentration, pressure, flow rate, voltage, and current. In controlled laboratory conditions (indoor) butane gas was used as an approximation of the change in emissions, and capture efficacies of above 90% was obtained. Vacuum pump was controlled under adaptive PWM control and efficiency was estimated by comparing the $CO_2$ level before and after capture and especially at higher concentrations above 2,500 ppm. The performance of the prediction was evaluated based on a linear regression model that was trained on time series $CO_2$ data, and the model showed an $R^2$ value of 0.93. The experiments were performed at 298.15 K in stable conditions of ambient temperature and real-time recorded with the help of Blynk and Google Sheets.

The MH-Z19B gas sensor starts working by detecting $CO_2$ gas, but it is also sensitive to other gases like $NH_3$, benzene, and smoke. During testing, butane gas was used; therefore, the sensor is not reliable for accurately measuring $CO_2$ levels. Despite the sensor's capability to test $CO_2$ concentrations from 10 to 1,000 ppm, it produced results as high as 20,000 ppm and very low concentrations reaching 30 ppm under normal conditions. Not only that, but for the sensor to work accurately, it needs to be constantly calibrated, and it needs to be preheated for 24–48 h. With that being said, regardless of the results obtained, the sensor is effective in detecting gas in general, but for $CO_2$ specifically, a better fit will be sensors like MG-811, MH-Z19B, or CM1106SL-NS. These sensors were not used because of the testing difficulty of different stages, so for the prototype's sake, the MH-Z19B is suitable to test the system's main purpose of gas level testing and system adaptation.

When it comes to the pressure sensor, it was used to detect the pressure in the storage tank to calculate an estimate of how much $CO_2$ is stored. Unfortunately, the storage tank was not pressurized; therefore, the gas was not stored properly, and pressure was not created for the sensor to detect. Due to safety reasons to avoid storage tank explosion due to pressure, the system was simulated to increase storage whenever the vacuum air pump stops working, giving inaccurate and unrealistic results. Also, an alternative can be used with the Raspberry Pi model where a more advanced model like the Raspberry Pi 4 or 5 can be used, allowing opportunities to introduce advanced features like integrating machine learning and artificial intelligence into the system due to more storage, higher RAM, and better CPU performance.

Other than that, the system's main objectives were met, as it detects the changes in gas levels, controls the vacuum air pump speed, triggers an alarm system, and predicts future emissions based on detection trends while simultaneously updating Google Sheets with all the parameters measured and calculated and updating the Blynk dashboard for live monitoring. In this project there are areas where component choices could have been better, and execution might've been more precise, but overall, the system is reliable and accurate.

As for the system's SWOT analysis, the system has many strengths, including having an effective adaptation of the vacuum air pump speed corresponding to the changes in $CO_2$ levels, accurate $CO_2$ predictions using linear regression models that follow trends, an alarm system set in cases of hazardous emissions, and also having real-time monitoring features through the Blynk platform and live data logging in Google Sheets. Contradicting that, the project is not specified for $CO_2$ detection, but it is sensitive to different gases; the storage tank being unpressurized resulted in unreliable stored gas readings, and the system is not scalable to industry levels.

However, the system has opportunities to improve by using precise and specific sensors that are industrial grade, integrating advanced features like machine learning and artificial intelligence with different versions of Raspberry Pi, adding chemical absorption techniques to optimize absorption, and finally using a sealed storage tank and a provisional tank for gas storing with safety valves. With these improvements, threats like loss of internet connection can still affect the system reliance, as the Blynk dashboard and Google Sheets will stop updating, and the absorption of external gases can cause vacuum damage due to overload and the possibility of storage explosion due to different pressurized gases that can react in such environments.

One significant shortcoming of the prototype is the lack of a physical or chemical separation media, e.g., aminebased sorbent, membranes or adsorption media. Consequently, the system fails to do selective $CO_2$ separation or long term storage. Subsequent applications will incorporate sorbent-based capture system and sealed, pressure-rated containers so that carbon capture and storage could be experimentally verified but the proposed IoT-based adaptive control framework may be maintained. Any broader environmental or societal impact remains speculative and dependent on future integration with validated capture technologies. Although the proposed system was proven on a prototype level, its modular nature will allow it to be scaled to industrial use. The prototype container can be substituted with larger sealed and pressurized storage tanks containing certified safety valves, and industrial-grade $CO_2$ sensors can enhance the accuracy of measurements. Also, it is possible to upgrade the Raspberry Pi platform to more-performance models to run advanced analytics and machine learning. The inclusion of other existing industrial supervisory control and data acquisition (SCADA) systems would also facilitate easy implementation in power plants, cement factories and oil and gas facilities.

## 10. Conclusion

The proposed system is modular, which means that it is easy to scale it to industrial applications. Industrial grade $CO_2$ sensors, a sealed pressure rated storage vessel and a high-capacity vacuum system can be used in place of prototype components. It would be integrated with current SCADA and industrial IoT to allow implementation in power plants, cement plants, and oil and gas plants. Due to the increase in carbon emissions, our environment is disturbed as a result of the actions we take. Therefore, implementing this project is a step towards reviving the earth, because what can be measured can be managed. The Smart IoT-Based Adaptive Carbon Capture Control Framework has an environmental significance, as it reduces carbon footprint by neutralizing the carbon emissions, as well as a technical significance, as the system is optimized using IoT-based platforms and automation techniques to ensure maximum efficiency and effectiveness. The system is built as a monitoring device and a way to enhance post-combustion carbon capture techniques by using gas, flow, current, voltage, and pressure sensors to input data to the Raspberry Pi. Using MobaXtrem, a Python program is built to run through the Raspberry Pi, where the speed of the capture rate is controlled by PWM signals with duty cycles proportional to the amounts of $CO_2$ detected, and in cases of high emissions where the $CO_2$ levels exceed 2,500 ppm, logic is executed to trigger an alarm system. The data collected by the gas sensor is stored, and based on that, the linear regression model uses the polyfit function to predict future emission levels. Simultaneously, the data collected and system outputs are monitored in real time through the Blynk dashboard and in Google Sheets, where live data logging with time stamps happens every 3–5 s max. a system combining live monitoring features, automation, and predictions, allowing users to make better decisions in regard to finding solutions to lower emissions and ensuring that the emissions are neutralized by having the $CO_2$ get captured before spreading.

The drawbacks relating to the pressure sensor and the unpressurized storage tank had a great impact on the $CO_2$ estimation in the storage. In an attempt to solve this in future applications, it is suggested that a sealed and pressure rated storage vessel fitted with industrial pressure transducers and safety relief valves be employed. Also, it can be equipped with a dual-tank design that consists of a main storage tank and a temporary buffer tank which can provide safe pressure control and constant capture functionality. These advancements will allow the realistic buildup of pressure, precise mass calculation, and increased system safety.

Constraints were faced at different parts of the project where the readings were affected due to using a gas sensor instead of a $CO_2$ sensor and using butane gas for testing and having an unpressurized storage tank, which was due to safety reasons and lack of flow. These constraints were managed by simulating pressure and flow results that are realistic. Overall, the system has shown effectiveness, reliability, and adaptability. Future works include using industrial-grade sensors and chemical separation techniques to ensure that the gas absorbed is purely $CO_2$, more accurate testing techniques, and sealed and pressurized storage tanks in addition to a provisional tank, with both including safety valves. And finally, AI/ML techniques will be implemented for more advanced features, analysis, adaptability, and decision-making abilities. Future implementations will employ sealed, pressure-rated storage vessels equipped with industrial pressure transducers and safety relief valves. A dual-tank architecture comprising a buffer tank and main storage vessel is proposed to enable continuous capture while maintaining safe pressure limits. This work validates the sensing, control, prediction, and energy-aware actuation layers required for next-generation carbon capture systems. Although chemical separation and pressurized storage are outside the scope of the present prototype, the proposed framework provides a scalable foundation upon which industrial-grade capture mechanisms can be integrated. In conclusion, regardless of the constraints faced, the smart carbon capture has shown effectiveness and accuracy, reaching more than 90% capture relative efficiency.

## Author Contributions

Conceptualization, S.A.A.-Z. and S.A.H.; methodology, S.A.A.-Z. and S.A.H.; software, S.A.A.-Z.; validation, S.A.A.-Z., S.A.H. and M.P.; formal analysis, S.A.A.-Z. and M.P.; investigation, S.A.A.-Z. and S.A.H.; resources, S.K.; data curation, S.A.A.-Z.; writing—original draft preparation, S.A.A.-Z.; writing—review and editing, S.A.H., M.P. and S.K.; visualization, S.A.A.-Z.; supervision, S.A.H. and S.K.; project administration, S.K.; funding acquisition, S.K. All authors have read and agreed to the published version of the manuscript.

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The data presented in this study is available on request from the corresponding author.

## Conflicts of Interest

The authors declare no conflict of interest.

## AI Use Statement

During the preparation of this work, the authors used Claude and ChatGPT for language editing and grammar checking purposes. The authors subsequently reviewed and edited the content as necessary and take full responsibility for the final content of the published article.

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