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Automatic Control of Oxygen Flow for Hypoxemia Therapy Based on Fuzzy Method

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Abstract – *Hypoxemia is a serious condition that requires oxygen transfusion. Indiscriminate oxygen administration is a poor strategy that can increase organ damage and even death. This paper describes a system for automatically controlling airflow of an oxygen tubes to a patient based on blood oxygen saturation and respiratory rate measurements. The MAX30102 sensor is used to measure oxygen saturation levels, and the MAX9814 module is used to determine respiratory rate. Both sensor outputs are processed by an STM32F411 microcontroller, and then sent wirelessly to an Arduino Uno microcontroller, which implements the fuzzy logic controller to control oxygen flow The fuzzy output is used to activate a motor servo that controls the oxygen tube valve opening. The valve opening width (in degrees) is divided into 5 categories. Communication between the microcontroller and the valve actuator uses a 433MHz wireless RF module. The device test results revealed an MAE of 0.40% for oxygen saturation measurements compared to standard hospital measuring instruments and an MAE of 0.47% for respiratory rate measurements compared to manual measurements. Overall system testing produced a valve opening with an MAE of 0.56% compared to simulation results using MATLAB.*

Keywords: *Automatic control of oxygen flow, Blood oxygen saturation, Fuzzy logic controller, Hypoxemia, Respiratory rate*

I. Introduction

Hypoxemia, defined as a condition in which the level of oxygen in the blood is below normal, is a critical clinical problem that can lead to severe complications if not properly managed [1] [2]. It commonly occurs in patients with respiratory disorders such as chronic obstructive pulmonary disease (COPD), pneumonia, and acute respiratory distress syndrome (ARDS) [3] [4]. Oxygen therapy is widely used as a primary intervention to increase blood oxygen saturation (SpO_2) and prevent tissue hypoxia. However, maintaining an optimal oxygen flow rate remains a challenge in clinical practice due to the dynamic nature of patient conditions [1].

Conventional oxygen therapy systems typically rely on manual adjustment by medical personnel based on intermittent monitoring of oxygen saturation levels [5]. This approach has several limitations, including delayed response to rapid physiological changes, increased workload for healthcare providers, and the potential risk of human error. Inadequate oxygen delivery may result in either hypoxia or hyperoxia, both of which can negatively affect patient outcomes [6]. Therefore, an intelligent and automated control system is required to ensure precise and real-time regulation of oxygen flow.

Recent advances in biomedical engineering and control systems have enabled the development of smart oxygen delivery systems. Various control strategies, such as proportional-integral-derivative (PID) controllers and adaptive control methods, have been explored to regulate oxygen flow [7] [8]. However, these methods often require accurate mathematical modeling of the system, which can be difficult due to the nonlinear and uncertain characteristics of human physiological responses.

Fuzzy logic controller (FLC) has emerged as a promising alternative due to its ability to handle nonlinear systems and uncertainties without requiring an exact mathematical model [9]. By incorporating expert knowledge in the form of linguistic rules, FLC can mimic human decision-making processes in adjusting oxygen flow rates based on parameters such as blood oxygen saturation (SpO_2) levels and respiratory rate (RR). This makes FLC particularly suitable for medical applications where system dynamics are complex and not fully understood [10] [11].

In this study, an automatic oxygen flow control system for hypoxemia therapy based on the FLC is proposed. The system is designed to continuously monitor SpO_2, RR, and automatically adjust the oxygen flow rate in real time to maintain optimal SpO_2 levels. The proposed approach aims to improve patient safety, reduce the workload of healthcare providers, and enhance the efficiency of oxygen therapy. The performance of the system is evaluated through experimental validation to demonstrate its effectiveness in responding to varying hypoxemia conditions.

This paper is organized as follows: Section II presents the related work of the oxygen therapy. Section III describes the proposed system design, including hardware architecture and fuzzy control algorithm. Section IV discusses the experimental setup and results analysis. Finally, Section V concludes the paper and describes future research plan.

II. Related Works

Several studies have been conducted to control airflow rate in oxygen therapy. Sánchez-Morillo et al. presented a comprehensive review of physiological closed-loop control systems in intelligent oxygen therapy, highlighting the limitations of conventional manual oxygen delivery and the advantages of automated approaches. The study emphasized that closed-loop systems, which regulate oxygen flow based on real-time SpO_2 feedback, can significantly improve the time patients remain within target oxygen saturation levels while reducing clinician workload [6].

Oriol Roca et al. investigated the effectiveness of a closed-loop oxygen control system in patients with acute hypoxemic respiratory failure. The study demonstrated that automated oxygen regulation significantly increased the time patients remained within the target SpO_2 range compared to conventional manual adjustment, while also reducing the need for clinical interventions. Additionally, the system minimized episodes of hypoxemia and improved overall oxygen therapy efficiency. These findings highlight the potential of closed-loop control systems to enhance patient safety and optimize oxygen delivery in critical care settings [7].

The study by Sandal O et al. evaluated closed-loop oxygen systems in pediatric patients receiving high-flow nasal oxygen therapy. Results showed a significant improvement in maintaining SpO_2 within the target range (over 90%) compared to manual control (around 63%). The system also reduced fluctuations in oxygen levels and minimized clinician intervention [8].

Kaltsogianni et al investigated the effectiveness of automated oxygen regulation in maintaining optimal oxygen saturation levels in preterm infants. The results showed that closed-loop control significantly increased the time infants remained within the target SpO_2 range compared to manual oxygen adjustment, while also reducing episodes of hypoxemia and hyperoxemia. The system minimized fluctuations in oxygen levels and decreased the need for frequent clinical interventions. These findings demonstrate the potential of closed-loop oxygen control systems to improve safety and efficiency in neonatal respiratory care [12].

Recent research by AK Pal et al. on oxygen therapy regulation in Chronic Obstructive Pulmonary Disease patients, by developing a mathematical model of the respiratory system that considers the oxygen exchange delay time, as well as an intelligent control approach based on the Intelligent Set-point Modulated Fuzzy Model Reference Adaptive Controller (SFMRAC). Simulation results show that SFMRAC is able to provide better tracking performance and robustness compared to conventional methods, thus potentially increasing the effectiveness of automatic oxygen control systems in clinical applications [13]. Similarly, Radhakrishnan et al. developed a fuzzy predictive model for inspired oxygen based on physiological parameters, highlighting the importance of SpO_2-driven control [14]. In addition, Mehedi et al. introduced a fuzzy-PID approach that enhances system stability in respiratory control applications. This study confirms that fuzzy systems can achieve high accuracy (>95%) in respiratory-related predictions. These findings indicate that FLC is a robust and reliable approach for automatic oxygen flow control in hypoxemia therapy [15].

Similar to the research above, this study utilized a fuzzy controller to automatically regulate oxygen flow rate. The difference between this study and previous studies is this study used two biological parameters, SpO_2 and RR simultaneously, as FLC inputs. Comparing this research to the research by Mazaya et al., there are striking differences. Mazaya's research used FLC with SpO_2 and heart rate inputs to classify the level of hypoxemia, whereas in this study, the FLC inputs were SpO_2 and RR to control the oxygen flow rate in hypoxemia therapy [16].

III. Proposed System Design

The system consists of three main components: (1) physiological signal acquisition, (2) processing and control unit, and (3) oxygen delivery actuator. Physiological parameters, including SpO_2 and RR, are continuously monitored using non-invasive sensors (MAX30102 and MAX9814). The acquired signals are processed by a STM32F411 microcontroller, and send to Arduino Uno controller wirelessly. Arduino Uno will implements a fuzzy logic control algorithm to determine the appropriate oxygen flow rate according to SpO2 and RR values.

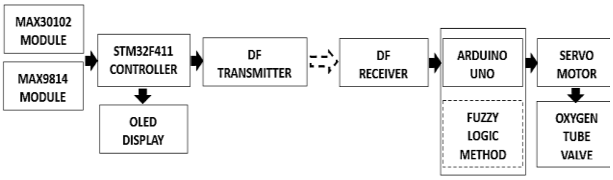


Fig. 1. System design

The output of the control system is used to adjust an oxygen flow valve actuator, therefore the closed-loop configuration enables continuous feedback between patient condition and oxygen delivery from oxygen tubes.

This system will ensure that the oxygen supply is dynamically adjusted according to the patient's needs.

A. Respiratory rate measurement

RR is an important physiological parameter that reflects the patient's breathing condition and is often associated with hypoxemia severity. In this study, RR is measured using a non-invasive sensor MAX9814. This sensor detects the periodic expansion and contraction of the chest or air flow during the respiratory cycle by detecting the sounds produced during the inspiration and expiration processes.

The acquired signal is processed using filtering techniques to remove noise and motion artifacts. Peak detection or zero-crossing methods are then applied to calculate the number of breaths per minute (BPM). The respiratory rate is used as one of the input variables for the fuzzy controller, providing additional information about the patient's respiratory status and helping improve the accuracy of oxygen flow adjustment. The schematic diagram of MAX9814 – RR module is shown on Fig. 2.

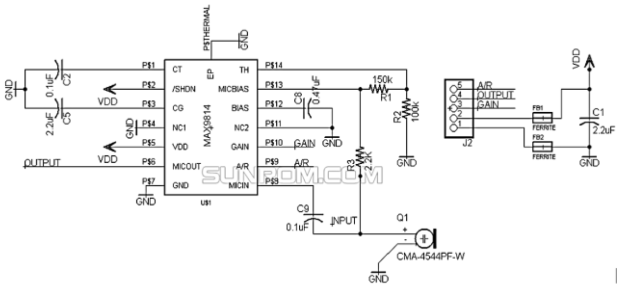


Fig. 2. MAX9814 – RR module [17]

B. Oxygen saturation measurement

SpO₂ is the primary parameter used to assess the oxygenation level in the blood. In this system, SpO₂ is measured using a pulse oximeter sensor MAX30102 based on photoplethysmography (PPG). The sensor operates by emitting light at two different wavelengths (red LED 660nm and infrared LED 940nm) and measuring the absorption differences to estimate the percentage of oxygenated hemoglobin.

The SpO₂ signal is continuously monitored and filtered to reduce noise caused by motion artifacts or poor sensor contact. By comparing how much red light and infrared light is absorbed, the MAX30102 can calculate what percentage of hemoglobin is carrying oxygen. The schematic diagram of MAX30102 – SpO₂ module is shown on Fig. 3, while the characteristics of light absorption by blood hemoglobin are shown in Fig. 4. Oxygenated hemoglobin absorbs more infrared light, while deoxygenated hemoglobin absorbs more red light.

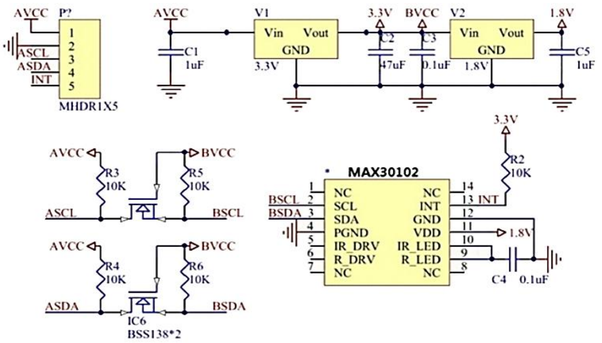


Fig. 3. MAX30102 – SpO₂ module [18]

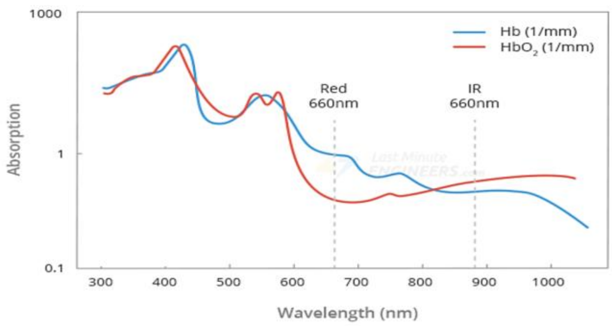


Fig. 4. Light absorption by hemoglobin [19]

If H_b is the level of deoxyhemoglobin and H_bO_2 is the level of oxyhemoglobin in the blood, then the oxygen saturation level in the blood, SpO₂, can be calculated using Eq. (1).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Y_i - \hat{Y}_i\right|$$

$$S_pO_2 = \frac{HbO_2}{Hb + HbO_2} \tag{1}$$

To obtain the SpO₂ value using the MAX30102 sensor, the pulsatile AC component (ac_{red} and ac_{ired}), which is influenced by heart rate, and the DC component (DC_{red} and DC_{ired}), which is the constant output signal for each infrared and red signal absorption, must be measured. Then, the absorbance ratio between red and infrared light waves, R, can be calculate using Eq. (2).

$$R = \frac{\left(\dfrac{ac_{red}}{DC_{red}}\right)}{\left(\dfrac{ac_{ired}}{DC_{ired}}\right)} \tag{2}$$

The raw output signal MAX30102 sensor is separated into ac and DC components using Eq. (3) and Eq. (4). And, then the SpO₂ value is obtained using an empirical approach, following Eq. (5).

$$DC = \frac{1}{N}\sum_{i=0}^{N-1} raw_{t-i} \quad (3)$$

$$ac = raw - DC \quad (4)$$

$$S_pO_2 = 110 - 25R \quad (5)$$

Where raw_{t-i} is the sensor output at $t - i$ (previous), N is the number of raw data averaged, DC is the average value (DC component value) and ac is the ac component value.

SpO_2 value is compared with a predefined target range to determine the patient's oxygenation status. This parameter serves as the primary input for the FLC, as it directly reflects whether the patient is experiencing hypoxemia.

C. Fuzzy logic controller design

The core of the proposed system is a FLC, which is used to determine the appropriate oxygen flow rate based on SpO_2 and RR inputs. FLC is chosen due to its ability to handle non-linear systems and uncertainty without requiring an exact mathematical model. The FLC consists of three main stages: fuzzification, inference, and defuzzification.

The input variables, SpO_2 and RR, are converted into linguistic variables using predefined membership functions. Each input variable is represented by five membership functions to capture different physiological conditions, as shown on Fig. 5 and Fig. 6.

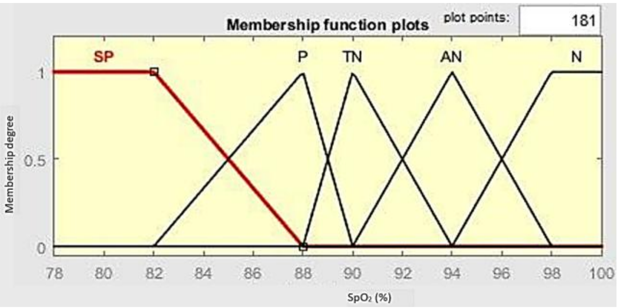


Fig. 5. Membership function of SpO_2

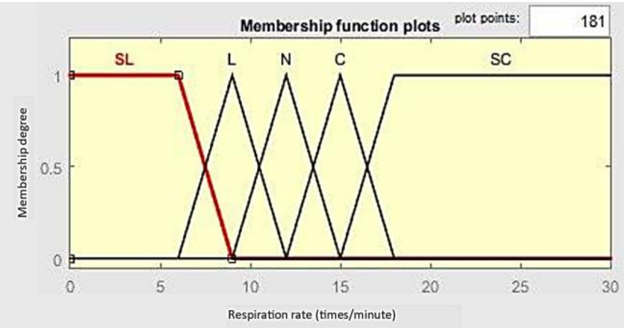


Fig. 6. Membership function of RR

The linguistic variables and their range in the SpO_2 and RR input are shown on Table I and Table II. While, the FLC output section that controls the oxygen flow rate and implemented as the oxygen tube valve opening degree is grouped into membership functions as shown in Table III. Determining the valve opening width uses direct observation of the oxygen cylinder by considering its rotation and minute oxygen output. A volume meter is installed on the oxygen cylinder valve therefore the minute oxygen flow rate when the valve is open at a certain degrees can be manually measured. The valve opening angle and oxygen flow rate are presented in Table III.

TABLE I
VALUE AND LINGUISTIC VARIABLES OF S_pO_2 INPUT

Linguistic variables	**Description**	**Value (%)**
SP	Very low	0 – 88
P	Low	82 – 90
TN	Abnormal	88 – 94
AN	Somewhat normal	90 – 95
N	Normal	94 – 100

TABLE II
VALUE AND LINGUISTIC VARIABLES OF RR INPUT

Linguistic variables	**Description**	**Value (%)**
SL	Very slow	0 – 9
L	Slow	6 – 12
N	Normal	9 – 15
C	Fast	12 – 18
SC	Very fast	15 – 30

TABLE III
VALUE AND LINGUISTIC VARIABLES OF OXYGEN FLOW RATE

Linguistic variables	**Description**	**Valve opening (degrees)**	**Oxygen flow rate (liters/minute)**
VL	Very low	0 – 30	0 – 1
L	Low	30 – 60	1 – 2
M	Medium	60 – 90	2 – 4
H	High	90 – 110	4 – 6
VH	Very high	110 – 140	6 – 10

Then, the fuzzy rule base is constructed using expert knowledge and clinical guidelines for oxygen therapy. A total of 25 rules (5×5 combinations) is defined, as shown on Table IV.

TABLE IV
VALUE AND LINGUISTIC VARIABLES OF S_pO_2 INPUT

SpO_2 \ RR	***SL***	***L***	***N***	***C***	***SC***
SP	H	VH	VH	VH	VH
P	M	M	H	VH	VH
TN	L	M	M	H	H
AN	VL	L	L	M	H
N	VL	VL	L	L	M

These rules enable the system to mimic the decision-making process of medical personnel. Finally, the fuzzy output is converted into a crisp value representing the oxygen flow rate (in liters per minute). If z is the oxygen flow rate, z_i and $\mu(z_i)$ are the sampling point and membership value at that point, then the formula of center of area used for defuzzification to obtain a smooth and stable output is shown on Eq. (6).

$$z = \frac{\sum z_i \mu(z_i)}{\sum \mu(z_i)} \quad (6)$$

The fuzzy controller continuously adjusts the oxygen flow rate based on real-time input data, forming a closed-loop system that maintains SpO_2 within the desired range while avoiding hypoxemia.

IV. Experimental Result and Analysis

This study was conducted on a laboratory scale, with 8 subjects in a sick condition and hypoxemia indicated (asthmatics, severe influenza, stroke, and lung disease) and 30 healthy subjects, some of whom conditioned as patients with abnormal respiratory conditions. Subjects were considered healthy if their $SpO_2 \geq 95\%$ and their RR was in the range of 12 – 20 breaths per minute. Table V shows the subjects distribution.

TABLE V
SUBJECTS DISTRIBUTION

Responden condition	Persons
Healthy	20
Healthy (conditioned with abnormal breathing)	10
Sick (indicated hypoxemia)	8

Sensor measurement results and overall system performance were statistically evaluated using Mean Absolute Error (MAE), as shown in Eq. (7).

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|Y_i - \hat{Y}_i\right| \quad (7)$$

Where N is the number of measurements, Y_i is the result of measurements using the proposed system and $\widehat{Y}_i$ is the result of measurements using a reference meter.

A. Oxygen saturation analysis

Measurements were conducted simultaneously using the reference meter and the sensor system. The reference meter was attached to the fingertips of the right hand, while the sensor was attached to the fingertips of the left hand. A trial placement of the sensors was conducted on the fingertips of the index finger, middle finger, and ring finger. The subjects were seated or lying quietly. The circuit and measurement results are shown in Fig. 7 and Table VI. SpO_2 measurements from 38 subjects produced SpO_2 levels in the range of 90% - 99%.

Based on Eq. (7), the measurement results with the sensor placement at the tip of the index finger produces an MAE of 0.4%, while the sensor placement at the middle fingertip produces an MAE of 1.2% and the sensor placement at the tip of the ring finger has an MAE of 1.6%. Therefore, the most effective sensor placement is at the tip of the index finger and the sensor will be placed at the index fingertip for next measurement.

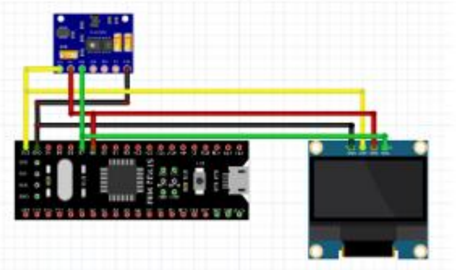
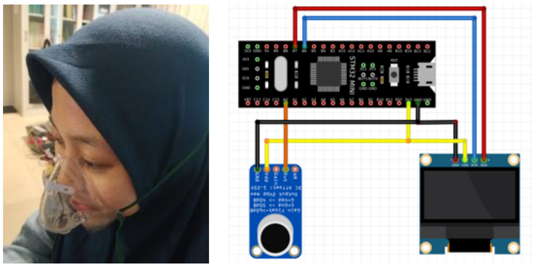


Fig. 7. Oxygen saturation measurement circuit

TABLE VI
SpO_2 MEASUREMENT RESULTS BASED ON SENSOR PLACEMENT

SpO2 on the reference meter (%)	SpO_2 measurement (%) with sensor placement on		
	Index fingertip	middle fingertip	ring fingertip
90	90	90	90
91	91	90	90
92	91	91	90
93	92	91	91
94	93	93	92
95	95	94	93
96	96	95	94
97	98	96	96
98	98	96	96
99	99	97	97

When the sensor is placed on index fingertip, normal oxygen saturation measurements (95%-99%) give an MAE of 0.2%, while abnormal oxygen saturation (<95%) produce an MAE of 0.6%. Both errors are quite small, indicating that the oxygen saturation measurement using the developed system provide accurate result and medically acceptable.

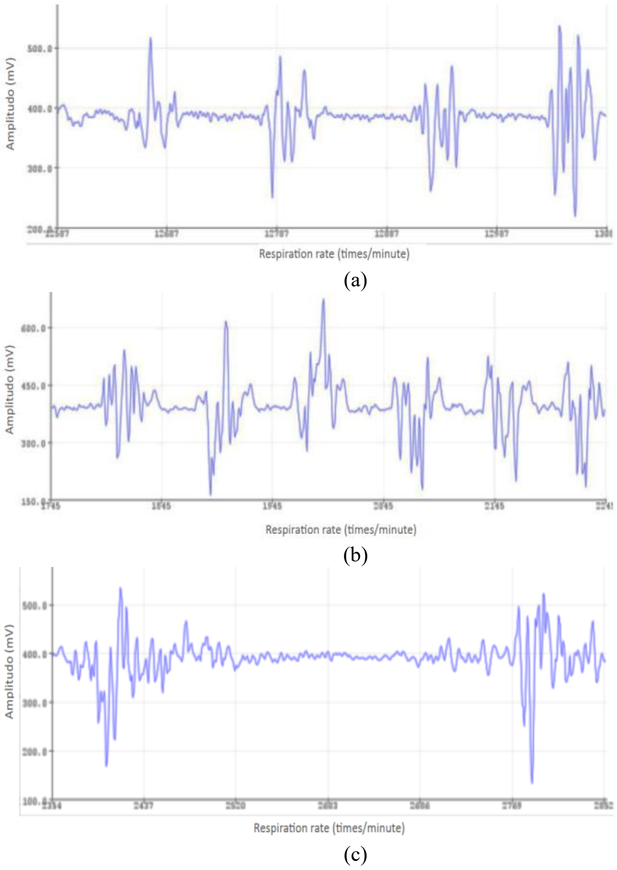


(a) Sensor placement (b) RR measurement circuit

Fig. 8. RR measurement

B. Respiratory rate analysis

Measurements are made by placing the sensor near the nostrils inside a mask therefore the sensor detect the inspiration and expiration sounds clearly, as shown on Fig. 8. The respiration measurements under normal, fast, and slow breathing conditions are shown in Fig. 9. The inspiration sounds have maximum amplitude of 320 mV while expiration sounds produce minimum amplitude of 480 mV. Measurements were conducted on 38 subjects, resulting in a respiratory rate (RR) of 8 – 23 breaths per minute.



(a)

(b)

(c)

Fig. 9. Output signal of RR measurement (a) Normal breathing signal, (b) Fast breathing signal, (c) Slow breathing signal

TABLE VII

MANUAL RR MEASUREMENT AND USING THE PROPOSED SYSTEM

Measurement (times/minute)		Error (%)
Manual	**Proposed system**	
8	8	0.13
10	9	0.2
11	11	0
12	11	0.08
13	12	0.08
14	14	0
15	14	0.07
16	16	0
17	17	0
18	17	0.06
19	18	0.05
20	20	0
21	20	0.05
22	22	0
23	23	0

Low RR was observed when subjects were calm, resting, or sleeping. High RR was observed when subjects (in healthy conditions) had completed strenuous activity or exercise. High RR was also observed in subjects with illness (asthma, severe influenza, and other lung diseases). Then, the automatic RR calculation by the proposed system is validated with the manual measurement, as shown on Table VII.

Using Eq. (7), MAE of RR measurements are 0.47%. RR calculation errors are mostly caused by incorrect sensor installation therefore it cannot detect breathing sounds clearly and the voltage produced by expiration and inspiration does not reach the threshold.

C. *Data transfer testing*

The 433MHz RF module is configured into two device, the first module serves to transmit data (RF – Tx), while the second module to receive data (RF – Rx). The results of RR and SpO_2 displayed on the OLED monitor will be sent via RF – Tx to the RF – Rx. Data packet transmission experiments were conducted using an RF module with varying Tx and Rx distances. Table VIII shows that the RF module can transfer data accurately when the Tx and Rx distance is less than 3 meters. This distance is sufficient to place the oxygen tubes a maximum of 3 meters from the patient without interfering with other medical procedures.

TABLE VIII

VALUE AND LINGUISTIC VARIABLES OF S_PO_2 INPUT

Data on OLED RR (x), SpO2 (%)	Data on Arduino RR (x), SpO2 (%)	Loss (%)	Distance (m)
RR = 0, Spo2 = 98	RR = 0, Spo2 = 98	0	0.30
RR = 14, Spo2 = 99	RR = 14, Spo2 = 99	0	0.50
RR = 23, Spo2 = 98	RR = 23, Spo2 = 98	0	0.50
RR = 20, Spo2 = 99	RR = 20, Spo2 = 99	0	1.00
RR = 19, Spo2 = 99	RR = 19, Spo2 = 99	0	1.50
RR = 22, Spo2 = 98	RR = 22, Spo2 = 98	0	2.00
RR = 23, Spo2 = 96	RR = 23, Spo2 = 96	0	2.10
RR = 16, Spo2 = 98	RR = 16, Spo2 = 98	0	2.20
RR = 20, Spo2 = 94	RR = 20, Spo2 = 94	0	2.20

D. *Fuzzy logic controller analysis*

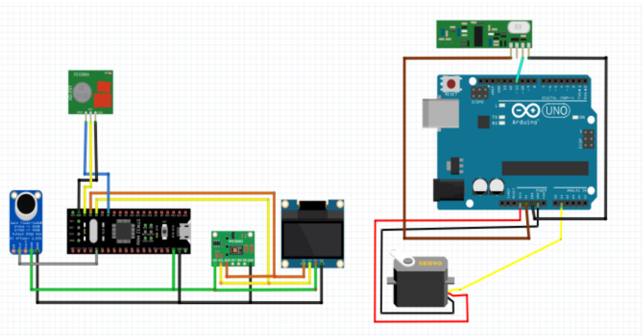
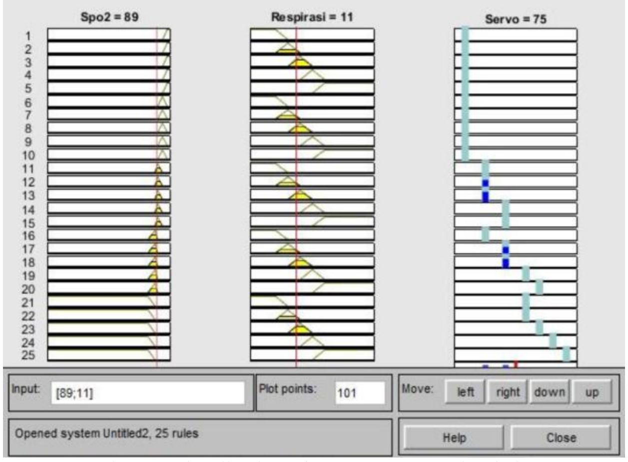


Fig. 10 Integrated system circuit

In the FLC function test, all modules have been integrated, as shown in Fig. 10. The results of SpO_2 and RR data processing by the STM32F411 Processing Unit are sent wirelessly to the Arduino Uno controller unit to be processed using FLC. The FLC output is used to adjust the valve opening degree, which automatically determines the volume of oxygen released. The wider the valve opening, the greater the volume of oxygen released.

The FLC output was validated using MATLAB's FLC simulation Rule Viewer. An example of a MATLAB simulation is shown in Fig. 11 (inputs of SpO_2 = 89% and RR = 11 times/minute, resulting in a servo motion output of 75 degrees). MATLAB simulation as a reference is set at an input SpO_2 of 90% - 99%, input RR of 8 – 24 times/minute and produces servo rotation output in the range of 0 - 140°.



Spo2 = 89

Respirasi = 11

Servo = 75

Input: [89;11]

Plot points: 101

Opened system Untitled2, 25 rules

Fig. 11. Visualization of FLC MATLAB simulation

Fig. 12 is a visualization of the overall system output performance (servo motor rotation degrees). Comparison of the FLC simulation output using MATLAB and the proposed system output produces an MAE of 0.56%. The evaluation results demonstrate that the controller effectively regulates a stable oxygen flow.

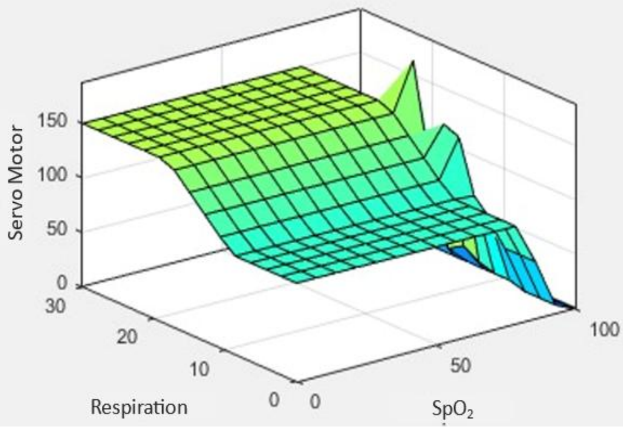


Fig. 12. Performance of servo motor based on SpO_2 and RR

The proposed system also achieved an average response time of 12 seconds to achieve a stable valve opening, This indicates a rapid response in anticipating the patient's condition. The smoothness of the oxygen valve opening indicates that the FLC successfully avoids abrupt changes in SpO_2 and RR, thereby improving patient safety and comfort. Therefore, this proposed system highly suitable for future development and implementation as an IoT-based medical devices.

V. Conclusion

The proposed fuzzy logic-based oxygen flow control system has demonstrated effective performance in managing hypoxemia conditions by regulating oxygen delivery based on SpO_2 input and RR inputs. SpO_2 measurements using the MAX30102 sensor placed on the index fingertip resulted in a MAE of 0.40%. Meanwhile, RR measurements using MAX9814 sensor to detect breathing sounds resulted in a MAE of 0.47%. Both sensor outputs are processed by the STM32F411 Processing Unit and sent to the Arduino Uno Controller Unit wireless using the 433MHz RF module.

The implementation of a fuzzy logic controller to regulate the oxygen tube valve opening using a servo motor resulted in a MAE of 0.56%. The evaluation results demonstrate that the controller effectively regulates a stable oxygen flow. The smoothness of the oxygen valve opening indicates that the FLC successfully avoids abrupt changes in SpO_2 and RR. Therefore, this proposed system is highly suitable for future development and implementation as an IoT-based medical devices.

However, this study has several limitations. One of the main constraints is the difficulty in obtaining subjects with SpO_2 levels below 90%, which limits the validation of the system under severe hypoxemia conditions. As a result, the system performance in critical scenarios still requires further investigation using a broader dataset. Future work should focus on incorporating clinical data from hypoxemic patients and improving system robustness for real-world medical applications.

Conflict of Interest

No Conflict of Interest. The authors declare that they have no conflict of interest regarding the publication of this paper.

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