UNIVERSITY OF RWANDA
COLLEGE OF SCIENCE AND TECHNOLOGY
AFRICAN CENTRE OF EXCELLENCE IN INTERNET OF THINGS

DESIGN AND APPLICATION OF THE FUZZY LOGIC OPTIMIZATION TECHNIQUE IN EARLY FIRE DETECTION FOR LOW-COST FIRE DETECTION SYSTEMS USING THE IoT BASED PLATFORM

A Case Study of Local Urban Markets in East Africa (EA)

PhD. Thesis submitted in the fulfilment of requirements of award of PhD Degree in Internet of Things – Wireless Intelligent Sensor Networking.

Submitted by

Emmanuel Lule
(219008409)

20th September, 2024

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Thesis Supervisor: **Prof. Chomora Mikeka (PhD)**

Thesis Co-Supervisor(s): **Dr. Alexander Ngenzi (PhD)**

Dr. Didacienne Mukanyiligira (PhD)

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20th September, 2024

DECLARATION:

I hereby declare that the dissertation entitled "*Design and Application of the Fuzzy Logic Optimization Technique in Early Fire Detection for Low-Cost Fire Detection Systems Prototype Using the IoT Based Platform: A Case Study of Local Urban Markets in East Africa*" to be submitted for the Degree of Philosophy is my original work and the dissertation has not formed the basis for the award of any degree, diploma, associateship or fellowship of similar other titles. It has not been submitted to any other University or Institution for the award of any degree or diploma.

Emmanuel Lule

ELule

Date: Friday, 20th September, 2024

Emmanuel Lule, a Ph.D. student of UR-ACEIoT 219008409 successfully defended the thesis/dissertation entitled “DESIGN AND APPLICATION OF THE FUZZY LOGIC OPTIMIZATION TECHNIQUE IN EARLY FIRE DETECTION FOR LOW-COST FIRE DETECTION SYSTEMS USING THE IoT BASED PLATFORM”, which he prepared after fulfilling the requirements specified in the associated legislations, before the thesis examination members whose signatures are below.

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ABBREVIATION	**DESCRIPTION**
ACEIoT	African Center of Excellence in Internet of Things
AI:	Artificial Intelligence
API:	Application Programming Interface
ANFIS:	Adaptive Neural Fuzzy Inference System
ANN	Artificial Neural Networks
BMM	Begian-Melek-Mendel
CBD	Central Business District
CMM:	Confusion Matrix Model
CNN:	Convolution Neural Networks
CSV:	*Comma Separated Value
EFIP:	Estimated Fire Intensity Prediction
eKM	enhanced Karnik Mendel, Type Reduction algorithm
EA:	East Africa
CO:	Carbon Monoxide
CO_2:	Carbon dioxide
O_2	Oxygen
IoT	Internet of Things
IR:	Infra-Red Flame
IT2:	Interval Type -2 Fuzzy Systems
IDE:	Integrated Development Environment
FAM	Fuzzy Associative Memory (Matrix)
2FAM	Second Order Fuzzy Associative Memory (Matrix)
FLC:	Fuzzy Logic Controller
FCS:	Fuzzy Control System
FIS:	Fuzzy Inference System
FS:	Fuzzy Sets
FI:	Fire Intensity
FOU:	Footprint of Uncertainty
GCE:	Gas Combustion Efficiency
LDC:	Least Developing Countries
LED:	Light Emitting Diode
LDR:	Light Dependent Resistor
LMF	Lower Membership Function
UMF	Upper Membership Function
TSK:	Tang Sugeno Kang
MF:	Membership Function
MAE:	Mean Absolute Error
MSE:	Mean Square Error
MCU:	Micro Controller Unit
MQTT:	Message Queue Telemetry Transport
ML:	Machine Learning
RMSE:	Root Mean Square Error
TR:	Type Reduction
T1, T2:	Type-1, Type-2 Fuzzy Systems
QoS:	Quality of Service
OHSA:	Occupational Health and Safety Act
WSN:	Wireless Sensor Networks
WSAN:	Wireless Sensor and Actuator Networks

MATHEMATICAL SYMBOLS AND DESCRIPTION

$\wedge$: Minimum Operator,

$\vee$: Maximum Operators and,

$\sqcup$: Joint Operation

$\overline{\boldsymbol{\alpha}}_{\boldsymbol{i}}$: The firing strength of the matching degree of similarity s and antecedent x_j , using a t-norm operator*

$\subseteq$: Defines a set A as subset of element of set E, such that $A \subseteq E$

(F, A): A pair called the soft set over U, where F is a mapping given by: F: A → P(U).

For ε Є A: F(ε) is defined as a set of ε- approximate elements of the soft set (F, A).

$\mu_{\tilde{A} \text{ u } \tilde{B}}(x)$, $\mu_{\tilde{A}}(x)$, $\mu_{\tilde{B}}(x)$: are the secondary membership functions and all belonging to Mamdani's type-1 fuzzy sets representing Union, Intersection and Compliment for the proposed IT2 TSK model design.

U: Initial universe of objects or a finite and non-empty set U

Jx: Secondary Domain Values represented from of [0 -1]

F(ε): A Set of Approximate Elements of the Soft Set (F, A).

R^2 The Coefficient of Determination

μ: Type-2 Membership Function

P(U): Defines the power set of U such that: $A \subseteq E$.

E_U: The set of parameters about the objects modelled

X: The primary domain with input x

ABSTRACT

East Africa's local markets, such as Owino, Uganda; Gikomba, Kenya; and Gisozi, Rwanda, have faced a high prevalence of uncontrolled fire accidents. Electrical circuits, arson, fuel spillage, and charcoal stoves are among the major causes of fires. Currently, fire departments have not developed any contingency plans for the management and control of fire accidents. And there are no early warning systems to monitor and control fires before becoming uncontrollable. Instead, human patrol methods are used to monitor these fire incidents, which are ineffective, insufficient, and obsolete. However, if these fires are not managed and controlled properly, market occupants and the nearby community face a high risk of severe property damage and loss of life. According to studies on unit smoke, flame detectors are unreliable, making them highly prone to false alerts. Additionally, satellite systems in developing countries are highly expensive to purchase and operate and cause unnecessary delays because of their lengthy scanning cycles for fire detection.

The study utilized the MATLAB 2018a fuzzy toolbox and Arduino (IDE) software to design and develop a hardware solution for a low-cost IoT-enabled fire detection system for local markets, yielding three major contributions:

A fuzzy-based detection model for early fire detection to aid public safety and control in local markets is proposed. Using MATLAB, six input parameters, i.e., temperature, humidity, flame, CO, CO_2, and O_2, are used vis-à-vis EFIP. Results show that, the obtained solution achieved an EFIP output accuracy of 95.83% using fuzzy inference rules. Hence, the study helps firefighting professionals and fire rescue departments understand the significance of fire control systems, with the primary goal of minimizing related fire risks and damage through the use of early warning systems.

Secondly, an Interval Type-2 (IT2) Tang Sugeno Kang (TSK) fuzzy model for intelligent fire intensity detection algorithms with decision-making in low-power devices is proposed using a free open-source IT2 MATLAB toolbox. Results show that the model exhibited an accuracy rate of 98.2%, with MAE = 1.3010, MSE = 1.6938, and RMSE = 1.3015. Thus, this study serves as the basis for the development of in-built low-power fire detection systems that are economical, replicable, and quickly deployable for usage by the firefighting personnel in LDCs, with the major objective of safeguarding extremely dangerous urban marketplaces and public gazette areas from fire accidents.

Thirdly, a hardware solution for a low-cost IoT-enabled fire detection system using fuzzy application methods is presented. Using the Arduino IDE, results demonstrated an accuracy of 91%, evaluated using the confusion matrix model. Hence, the study is significant for firefighting professionals as a foundation for a new approach to low-cost fire detection to respond to them urgently and quickly through providing early warning notifications and calling for quick action in case of a fire accident.

In conclusion, because of the extensive fire outbreaks and a lack of effective fire control methods, the study focused on local markets particularly, in Uganda. Existing manual techniques lead to severe damage from unnecessary delays in calling police agencies. Hence, the study proposed a hardware-based solution for a low-cost fire detection system using fuzzy reasoning to enhance early warning notifications, improve decision-making, and minimize false alerts. Future work encourages rigorous fire safety risk assessments, fire safety management, and appropriate control and suppression procedures for the markets by investigating the level of fire dangers, associated risks, and threats and evaluating the damage and expenses realized. This contributes to accurate fire risk assessment models, appropriate fire safety laws, best practices in fire safety management, and control techniques.

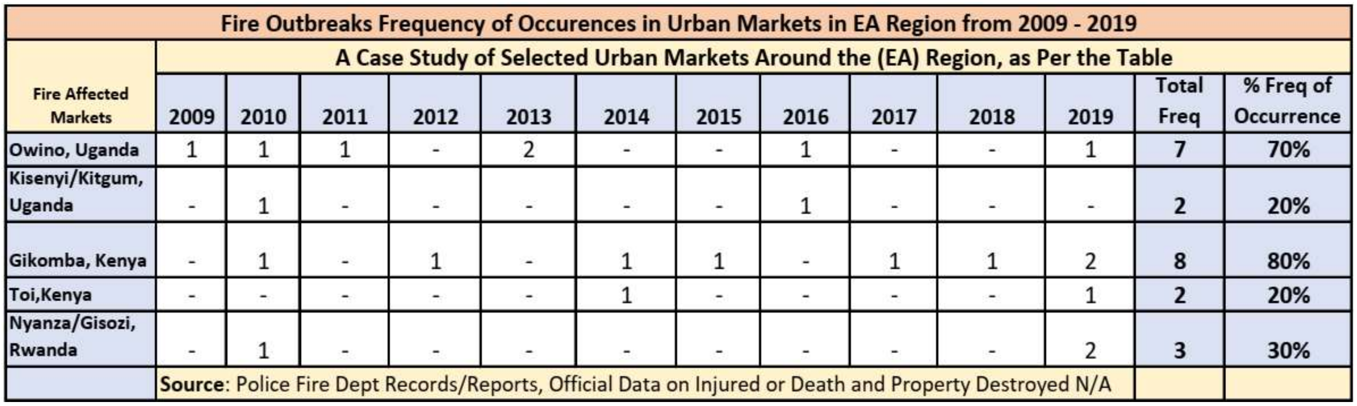
CHAPTER 1

INTRODUCTION

1.1 Background Information

Disaster phenomena i.e., fires, floods, epidemic diseases, gas pollution, and frequent landslides are some of the major hindrances to human civilization apparently emerging with accelerating urbanization[1][2]. Among the prior disasters mentioned, for example, fire outbreaks greatly affect the local urban markets located in the Central Business District (CBD) of East Africa (EA). For instance, St. Balikudembe market in Uganda, popularly known as "Owino," employs over 500,000 low-income earners who trade in mainly small-scale businesses comprising food, second-hand clothes and bags, shoes, textiles, and local traditional medicines, among others, for their day-to-day livelihood. The major fire incidents between 2009 and 2019 are summarized in **Fig. 1.1**. According to Uganda Police reports, the main causes of such fires are electrical short circuits, suspected arson, fuel or gas spillage, and carelessly neglected charcoal stoves[3][4]. Hence, the market community faces a major risk of loss of life and property worth millions as a result of such uncontrolled fires.

1.2 Summary of Fire Outbreaks Occurrences in Local Markets of (EA) (2009-2019)



Fire Outbreaks Frequency of Occurences in Urban Markets in EA Region from 2009 - 2019													
	A Case Study of Selected Urban Markets Around the (EA) Region, as Per the Table												
Fire Affected Markets	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	Total Freq	% Freq of Occurrence
Owino, Uganda	1	1	1	-	2	-	-	1	-	-	1	**7**	**70%**
Kisenyi/Kitgum, Uganda	-	1	-	-	-	-	-	1	-	-	-	**2**	**20%**
Gikomba, Kenya	-	1	-	1	-	1	1	-	1	1	2	**8**	**80%**
Toi,Kenya	-	-	-	-	-	1	-	-	-	-	1	**2**	**20%**
Nyanza/Gisozi, Rwanda	-	1	-	-	-	-	-	-	-	-	2	**3**	**30%**
	Source: Police Fire Dept Records/Reports, Official Data on Injured or Death and Property Destroyed N/A												

Fig. 1.1: Detailed Summary of Selected Fire Outbreaks Occurences Existed in Local Urban Markets of (EA) Between the Period of (2009-2019)

Developing countries have shown minimal interest in the control, planning, monitoring, and detection of fire outbreaks. Despite previous encounters, no early warning systems have been deployed to monitor and detect fires in markets. The fire departments are largely underequipped and rely solely on the human patrol mechanisms of people calling fire brigades to monitor, detect, control, and extinguish fires. However, such methods are inaccurate because the fire department frequently arrives late at the scene. Also, there are no proper fire prevention and rescue mechanisms in place to protect against related fire disasters. Related challenges faced by the fire and rescue departments include: Delayed reporting of fire incidents, a lack of fire detection systems, and appropriate fire safety laws for the implementation of appropriate fire safety measures [5][6].

In conclusion, several studies on fire detection using fuzzy logic have been done. For instance, Muduli *et al.* [7] demonstrated a fuzzy-based WSN fire monitoring system for underground coal mines. Sensors are connected in an underground coal mine to monitor and collect data, like temperatures and gas concentration levels, which are then sent to a central processing sink. Temperature and gas concentrations, however, make Type-1 fuzzy systems more susceptible to error uncertainties compared to Type-2 fuzzy systems. Satellite systems [8][9] are costly to acquire and maintain. Also, they are liable to have long scanning cycles, leading to unnecessary delays. Unit-smoke detectors [10]or flame sensors are highly susceptible to false alerts. Hence, the proposed fire detection prototype is low-cost to ensure proper fire safety control through alarm notification and minimize extensive fire damage to save the lives and property of the market community.

1.3 Problem Statement

Local markets located within the central business district (CBD) of East Africa, i.e., Owino, Uganda; Gikomba, Kenya; and Gisozi, Rwanda, are continuously faced with a high prevalence rate of fire outbreaks. The major causes of these rampant fires are credited to electrical short circuits, suspected arson, fuel spillage, and carelessly neglected charcoal stoves, amid others[4][2]. Currently, there are no early warning systems to safeguard the market community against any fire-related calamities that may result in the loss of life and property. Existing methods, like unit smoke or flame detectors, are inaccurate and have a high susceptibility to false alarms. Also, satellite systems are also liable to long scanning cycles, leading to unnecessary delays. They are highly expensive to purchase and maintain for developing nations[11][12][13]. Sowah *et al.* [14] proposed a fire detection and notification system with Temp102 temperature, MQ2 smoke, and DF Robot flame sensors using a fuzzy-based algorithm to determine the "*state of fire*". Toledo *et al.*[15] proposed wireless sensor networks and fuzzy logic to estimate forest fire concerns in short term and also determine recent fire breakouts. The Analytical Hierarchy Process (AHP) method was used to provide accurate real-time fire spread and alerting using a mobile application. However, the proposed solutions in [14][15] do not consider the intensity of flame in real time for a given fire outbreak situation. Hence, this study seeks to develop a hardware prototype of an IoT-based fire detection system using fuzzy application methods to improve the rate of accuracy of low-cost fire detection systems through the provisioning of early warning notifications and an informed decision with minimal delays. In conclusion, the proposed solution benefits firefighters by laying the foundation for future low-cost, easily deployable fire detection systems for use by the local market community to ensure proper fire safety precautions are realized through immediate evacuation.

1.4 Study Area

The study focused mainly on Uganda for data collection, particularly the Owino market, as the major case study. The rest of the markets within East Africa (EA) were not considered for data collection due to the effects of COVID-19 as the major limiting factor for the study.

1.4 Research Aims

The aim of the thesis is to develop a hardware-based prototype of a low-cost IoT-based fire detection system using fuzzy application methods by determining an appropriate and informed decision through triggering a true fire alarm notification. The following objectives are defined based on the study questions stated in **Section 1.5** and the gaps identified in **Section 1.3.**

1. To design an IoT fuzzy detection model to aid early monitoring, detection and safety control using a fuzzy based technique to ultimately make an informed decision about the likelihood of a fire outbreak. This is realized through a decision classification evaluation using the fuzzy technique to establish the percentage risk of fire occurrence and significantly predict the "*fire status.*"

2. To design an Interval Type-2 (IT2) Tang Sugeno Kang (TSK) fuzzy model for intelligent fire intensity detection algorithm for decision making in low-power devices. This ensures an accurate and early fire detection is realized through improved decision-making in low-power

fire detection devices. The solution minimizes extensive damages through early notification mechanisms, saving lives and property in the nearby market community.

3. To implement of a hardware prototype of an IoT-based fire detection systems prototype using fuzzy application methods. The proposed solution is of low-cost and easily deployable by firefighting personnel to safeguard the market community against the potential dangers of future fire-related incidents.

1.5 Research Question(s)

The following study inquiries were addressed;

1. What is the threshold value for fire safety if a gradual change in temperature, humidity, gas, and smoke is realized?
2. What is the percentage accuracy of the proposed fire intensity detection algorithm?
3. What is the maximum, minimum, or threshold probability for a fire to be detected using the proposed fuzzy based fire detection solution?

1.6 Significance of the Study

The major justification of the research study can be observed in four significant ways:

1. To provide a platform for continuous monitoring, coordination, and control of fire outbreaks in local urban markets throughout the (EA) region as a main public safety and mitigation tool.
2. To assure quality of service (QoS) in monitoring systems while utilizing the limited bandwidth available to successfully communicate critical fire disaster information to data processing centers for immediate response.
3. To provide real-time analytical results relevant to stakeholders, the humanitarian community, and policymakers as a basis for appropriate decision-making in future fire disaster planning, management, coordination, and control.
4. Application of an intelligent fuzzy-based fire detection algorithm for decision making minimizes false alarms by precisely detecting the possibility of a fire outbreak, thereby boosting the effectiveness and efficiency of our suggested solution.

1.7 Thesis Overview and Contributions.

The research in the thesis is organized into six chapters and each of the chapter is dedicated into a specific goal clearly organized as follows:

Chapter 1: General Introduction that discusses the general frame work of the proposed study**.** Then **Chapter 2:** covers the literature on fire detection techniques using a variety of methods and the major limitations. Existing technologies for fire detection; satellite-based systems, camera-based systems, machine learning, and subsequently fuzzy logic for effective fire detection. Related works and the major limitation factors for its adoption. **Chapter 3:** Provides an IoT-based fuzzy detection model for assisting in fire safety and control in local urban markets. This addresses *objective* 1. The study proposed a fuzzy-based detection model for effective decision-making in early fire detection for a given "*fire status*" in order to ensure property fire safety control and protection in the local market community. Using the MATLAB 2018a software, we simulate the performance of the model, whose results are subsequently compared to previous proposed fire detection techniques.

Chapter 4: Designs an Interval Type-2 (IT2) Tang Sugeno Kang (TSK) model for the fire intensity detection algorithm that provides effective decision-making in low-power devices. This addresses *objective* 2. The proposed model is simulated using a free open-source MATLAB 2018a fuzzy toolbox, which results in a compared model. Furthermore, the study proposes an intelligent, lightweight fire intensity detection algorithm. **Chapter 5:** Provides an implementation of low-cost IoT-based fire detection systems prototype using fuzzy application methods. This addresses *objective* 3. Results are evaluated using a confusion matrix model (CMM) and compared with other related works. The proposed solution benefits firefighters by laying a foundation for future low-cost, easily deployable fire detection systems. It also allows firefighters to respond to fires more quickly and efficiently and **Chapter 6:** Limitations, Recommendations, Conclusion and Future Works.

CHAPTER 2

BACKGROUND THEORY

2.1 Fire detection and Monitoring in Uganda

Fire detection involves utilizing a system designed to detect combustion or its byproducts, which requires the use of an alarm notification signal, either audible or visual, to a corresponding signal in the remote-control center for prompt attention. Monitoring, is the rapid communication between the affected premises fire alarm system and the central command station [16]. The main benefit of fire monitoring is to save lives by alerting residents to the presence of a fire and allowing them to safely evacuate. In Uganda, for instance, fire monitoring for market areas has been seriously neglected due to mainly a lack of adequate warning systems in place for safety [17][6]. Likewise, the present situation relies heavily on human patrol observation methods, which are quite obsolete, inaccurate and incur unnecessary delays for early fire detection. This has had a huge impact in terms of the loss of lives and the destruction of property worth millions of shillings. Several methods and techniques have been used in fire monitoring all over the world, however, they face limitations when used in monitoring markets, as discussed in Section 2.2.

2.2 The Need for Fire Disaster Monitoring and Detection

The following are the primary reasons why fire early detection and monitoring are highly significant in today's society for proper fire control and management in order to ensure appropriate safety:

1. To offer timely fire disaster information to relevant stakeholders and the humanitarian community for use as a main public safety and mitigation tool.
2. To administer, control, plan, and coordinate all fire disaster monitoring efforts at the national level, as well as to give technical aid to the government by implementing future disaster relief and post-disaster assistance models.
3. To guarantee that fire disaster management is all-hazards focused, comprising of disaster risk reduction and an emergent response plan.

2.3 Review of Existing Technologies for Fire Monitoring and Detection

2.3.1 Internet of Things (IoT)

The International Telecommunication Union (ITU) defines it as a global infrastructure for the information society that enables improved services by interconnecting things using existing and evolving interoperable information and communication technologies[18][19]. Guicheng defined IoT the flow of information among multiple embedded computing devices using the internet as the mechanism of intercommunication[20]. In 2010 Qian Zhu *at el.,*[21], considered IoT as the third phase of information technology after internet and mobile communication networks, which is characterized by more extensive sense and measure, more comprehensive interoperability and intelligence. The technologies of IoT effectively facilitate the integration of material production and service management, the integration of physical world and the digital world. Therefore, IoT is a huge global information system composed of millions of objects that can be identified, sense, and processed based on standardized interoperable communication protocols. IoT technology has been applied in several application domains namely; smart cities, smart environmental, smart agriculture, intelligent transportation and smart homes, industrial IoT among others [22].

2.3.2 Satellite Based Systems:

In affluent countries, Earth-orbiting satellites have been used to monitor and identify forest fires. The advanced resolution radiometer (AVHRR) [23] launched in 1998 and the moderate resolution imaging spectrometer (MODIS)[24][25] launched in 1999 are used to collect satellite images in this technique. Unfortunately, these satellites can only offer images of the Earth's regions every two days, which is a lengthy scanning period for a fire occurrence [26]. For example, Anerao *et al.*,[11] developed a software for automatic detection of forest fire based on data points collected by NASA's MODIS (Moderate Resolution Imaging Spectro Radiometer). The MODIS contains data points classified into various bands. The software aims at detecting fire in the forest that is on land area. The band 3 of the MODIS is dedicated to lands. Therefore, data points are processed after extracting the band 3. The algorithm involves masking of water and cloud to get more accurate output. Masking is done to eliminate unwanted disturbance in the satellite image. Fire detection on satellite images is an important method. Three classes were industrial site that can be excluded based on their known location. This shows that satellite-based detection for forest fires has potential for fire control purposes provided that the supply of the infrared satellite data in day time is frequent. However, for least developing countries (LDCs), this technology is prohibitively expensive to purchase, implement, and maintain.

2.3.3 Wireless Sensor Networks:

WSNs are characterized in [1][11] as networks made up of small, low-cost nodes equipped with embedded processors and wireless communication capabilities that allow for flexible deployment and close monitoring of phenomena without the need for human involvement. WSNs have been successfully applied in several application domains namely; intelligent tracking systems, monitoring of the environment, military application to detect enemy battle zone, context-aware computing; using sirens to alert authorities for quick action. Several research teams have investigated the possibility of applying WSNs in disaster monitoring applications. For example, a study done by Sager *et al.*,[23][24], proposed an earthquake and tsunami warning system (TWS) that is used to detect tsunamis in advance and issues warnings to prevent loss of life and damage. The system is composed of two important components: a network of sensors to detect tsunamis and a communication infrastructure to issue timely alarms for possible evacuation from the coastal areas. The two types of tsunami warning systems are international and regional. Seismic alerts are used to instigate the watches and warnings; then data from the observed sea level height are used to verify the existence of a tsunami.

S. Aslan *et al.*, [25] suggested a fire detection system for libraries using WSNs. Since the library environment was vulnerable to fire threats due to the paper-based publications and the historical documents it contained. It was very important to ensure the safety of life and property in the libraries. Therefore, gas and smoke detection-based systems were used. In this study, using wireless sensor networks, a library fire detection system was designed and implemented on the Tiny-OS development platform. IRIS nodes and temperature sensors are used in the system. The designed system was tested in the library environment and generated an alarm response in 3 seconds compared to previous detection systems that respond in 30 s. In [26], Wireless Sensor Actuator Networks (WSAN) have been applied as a low-cost solution by several researchers in the monitoring of different applications like temperature control, indoor air quality, fire detection, and water ph. monitoring and control among others. In case of fire outbreaks, the major factors to be monitored are temperatures and relative humidity. When there is a sudden change in temperature and humidity an alarm is triggered to signal an early warning to the authorities for immediate action. Fortunately, this kind of method is appropriate for developing countries because it a low-cost solution to acquire and requires little or no maintenance as compared to satellite-based systems in [22][27].

2.3.4 Optical Sensor and Digital Cameras:

Nowadays, two different sensor networks are available for fire detection, camera surveillance, and wireless sensor networks. The development of sensor technology, digital camera, image processing, and industrial computers resulted in the development of a system of optical, automated early recognition and warning of forest fires. This method employs different types of sensors applied in terrestrial systems i.e., i. Video-camera, sensitive to the visible spectrum of smoke recognition during day and fire recognition during night, ii. Infrared (IR), thermal imaging cameras based on the detection of heat flow of the fire, iii. IR spectrometers, to identify the spectrometer's characteristics of smoke, iv. Light detection and ranging systems (LIDAR) detection of light and range that measure laser rays reflected from the smoke particles. The variant optical systems work with different algorithms which have the same concept in smoke and fire glow detection. The camera is used to simply produced images every while [28][27]. In[29] proposed an early fire detection framework using Convolutional Neural Networks (CNN) for CCTV surveillance cameras using a channel selection algorithm. Their experiment demonstrated a higher accuracy. In general, optical sensor camera systems are very expensive to deploy and maintain.

2.4 Fire Detection Using Machine Learning, Fuzzy Logic and Artificial Neural Networks (ANN) Technologies.

Soft Computing deals with approximate modeling of imprecise, uncertainty, partial truth, and approximations to provide solutions to real-life situations. In solving real-life problems, soft computing is based on several techniques namely; Machine Learning, Fuzzy Logic, Artificial Neural Networks, Genetic Algorithms, and Expert Systems specifically applied in automated systems control engineering[30].

2.4.1 Machine Learning (ML)

Machine learning is a subfield of computer science and artificial intelligence (AI) that uses data and algorithms to mimic how humans learn, gradually improving its accuracy. It primarily employs three types of algorithms namely; supervised, unsupervised, and reinforcement learning.

1. **Supervised Learning:** This type of machine learning feeds historical input and output data into machine learning algorithms, with processing added in between each input and output pair to enable the system to change the model and provide outputs that are as similar to the intended outcome as feasible.
2. **Unsupervised Learning:** Unsupervised learning does not apply the same labeled training sets and data as supervised learning, which requires humans to assist the machine in learning. Instead, the machine scans the data for less evident patterns. When you need to find patterns and use data to make judgments, this kind of machine learning is quite beneficial.
3. **Reinforcement Learning:** Reinforcement learning is the closest type of machine learning to how people learn. The algorithm used learns by interacting with its environment and receiving positive or negative reinforcement. Algorithms that are commonly used include temporal difference, deep adversarial networks, and Q-learning. Machine learning has been employed in a variety of domains, including fire detection; however, this research study focused primarily on the application of fuzzy logic for fire detection to effectively improve the accuracy for decision making using Interval Type-2 fuzzy based approach, to reduce the computational costs of Type-1 fuzzy control systems. Furthermore, fuzzy logic mimics human decision making by taking into account all conceivable values of "True" or "False." Machine learning, on the other hand, provides more intelligent decisions than fuzzy-based control systems. Machine learning, on the contrary, provides more intelligent decisions compared to fuzzy-based control systems.

2.4.2 Overview of Fuzzy Logic.

Fuzzy logic is a multivariate computing strategy based on the concept of "degrees of truth" rather than the traditional Boolean logic true or false, 0 or 1. It is concerned with approximate reasoning rather than fixed and perfect reasoning. Dr. Loft Zadeh pioneered the concept of fuzzy logic theory in 1965[34]. Fuzzy logic algorithms are; i) Frequently robust in the sense that they are not overly sensitive to changing settings and erroneous or forgotten rules; and ii) Simple to implement. ii). The fuzzy logic quantifies the certainty or uncertainty of established membership rules. Fuzzy logic has been used to generate new intelligent computing solutions in a range of domains, including decision-making, identification, pattern recognition, artificial intelligence, optimization, and control [35]. Fuzzy logic involves three stages namely; "***Fuzzification****":* The process of converting input variables into fuzzy values, and "***Fuzzy Inference Engine***": The process of utilizing fuzzy logic to create a mapping from a given input to an output. Membership functions, fuzzy logic operators, and if-then rules are used in the procedure. "***Defuzzification***": The process of creating a quantifiable outcome in crisp logic, given fuzzy sets and accompanying membership degrees [31]. The general architecture of a fuzzy logic control system is defined in Fig 2.1. below.

2.4.3 General Architecture of a Fuzzy Logic Controller (FLC)

Fig. 2.1 shows a general fuzzy logic controller with a fuzzifier that transforms a numeric expression (crisp input) into fuzzy data using a defuzzifier (crisp output), and an Inference engine that conducts the transforms based on a set of rules provided in the fuzzy data.

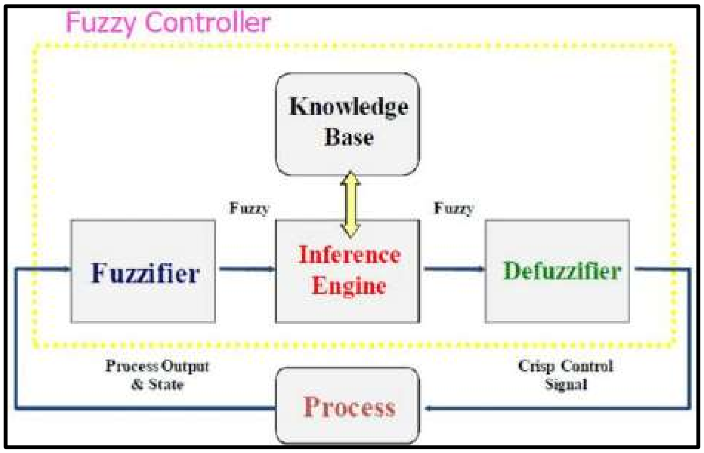


Fig. 2.1: General Architectural Overview of a Fuzzy Logic Controller (FLC) Design [32]

2.4.4 Practical Applications of Fuzzy Logic

i. Washing Machines: Washing machines are becoming increasingly common. These machines have advantages in terms of performance, productivity, simplicity, and cost. Sensors in this kind of domain continuously monitor the conditions inside the machine and alter operations to achieve the optimum wash outcomes. There is no standard for fuzzy logic because different machines operate differently. The washing process, water input, water temperature, wash time, rinse performance, and spin speed are all controlled by fuzzy logic. This extends the life span of the washing machine.

ii. Temperature Controller: Changes the speed of a heater fan by regular the two essential parameters i.e., temperature and humidity. Temperatures can be classified as; cold, cool, warm, or hot. There are three levels of humidity: low, medium, and high. Using the parameters, we can define our fuzzy sets.

2.4.5 Benefits of Fuzzy Logic

1. Fuzzy logic addresses applications perfectly as it resembles human decision making with the ability to make precise solutions from certain or approximate information.
2. It fills an important gap in engineering design left vacant by purely mathematical approaches e.g., linear control design, and purely logic-based approaches e.g., expert systems in systems design.
3. Fuzzy logic may accept the ambiguities of real-world human language and thinking. As a result, it provides an easy technique for specifying systems in human words, as well as automating the conversion of those requirements into practical models.

2.4.6 Artificial Neural Networks (ANNs), Genetic Algorithms and Expert Systems

ANNs, also known as neural computing, are large networks of integrated elements inspired by human neurons. The neural network has to be trained so that a set of known inputs produces the desired output. Training is done by feeding teaching patterns to the network and changing its weighted function according to previously defined learning rules. The learning can be *supervised;* the network is trained by giving inputs and matching output patterns, or *unsupervised*; the output of the network is trained to input patterns[30].

2.4.7 Benefits and limitations of ANNs

1. ANN are not universal tools for solving problems as there is no method for training and verification of the ANN.
2. The results of the ANN depend upon the accuracy of the input data and can also deal with incomplete data sets.
3. Excessive training is required for ANN complex systems design.
4. ANNs are successful in prediction and forecasting applications.

2.4.8 Genetic Algorithms

Genetic Algorithms are a type of artificial intelligence and fuzzy logic used in solve optimization problems in real world applications. Inspired by machine learning approaches, genetic algorithms can be used in finding solutions to complex search problems. For example, searching through design and components to find the best combination as the overall result. Therefore, genetic algorithms can be applied in a diverse range of applications including; Biomedical Engineering, Control Engineering, Climatology among others [30]. The basic processes in a generic algorithm are:

1. **Initialization:** In this phase the initial population is randomly created.
2. **Evaluation:** Each member of the population is evaluated and fitness assessed based on how well they fit the desired requirements.
3. **Selection:** Members fitting the desired requirement are only selected.
4. **Crossover:** New individuals are created by combining best aspects of the existing individuals at the end individuals closer to the desired requirements are created. The process is repeated from step (ii.) until a termination condition is finally reached.

2.4.8 Expert Systems

Also, called knowledge-based systems are computer-based systems that make intelligent solutions by emulating decision-making abilities of human experts. Expert systems are rule based systems that are part of artificial intelligence with ability to change their decision and make new decision. Examples of expert systems include; Financial Loan/Credit decision, Medical Diagnosis Systems, Robotics and Engineering Systems [30]. The main components of an expert system include;

1. **Knowledge Base:** The most important part of an expert system. This where the intelligence of the system is stored. Knowledge is acquired through sensors and knowledge is stored in if then else statements.

2. **Interface Engine**: The interface engine is between the knowledge base and the User. The interface engine makes decisions by following the conditions and requirements before it presents a desired solution to the user.
3. **User Interface:** Is usually in the form of natural language composed of everyday language such as Pascal, C and FORTRAN, also known as procedure languages. Other symbolic languages developed specifically for the expert systems include Lisp. Clips, Prolog and so on.

2.5 Related Works in Fire Detection Systems Using Fuzzy Methods.

State-of-the-art research has proposed the application of the fuzzy logic theory in solving a multitude of problems for intelligent decision-making. For example, G. Lavanya *et al*, [33] proposed an IoT-based fertilizer intimation system for smart agriculture using a fuzzy-based rule to monitor and analyze nutrients in the soil. The system utilizes the calorimetric principle by designing a novel Nitrogen-Phosphorus-Potassium (NPK) sensor with Light Dependent Resistor (LDR) and Light Emitting Diode (LED). Data sensed by the built NPK sensor from the chosen agricultural field is transferred to a Google cloud database for quick retrieval. The concept of fuzzy logic was applied to detect nutritional deficits using sensed data. During the fuzzification process, the crisp values of each sensed data are discriminated into five fuzzy values, namely very low, low, medium, high, and very high. A set of if-then rules is applied to each chemical solution for Nitrogen (N), Phosphorus (P), and Potassium (K). The Mamdani inference approach is then utilized to determine the shortage of N, P, and K in the soil structure. Ramzan *et al.*, [28] used a fuzzy logic technique to offer a multi-sensor intelligent solution for fire monitoring and warning systems in a smart building. The system analyzes data obtained from sensors to determine the presence of a fire in the structure buildings. The system then generates a real alert for additional fire control and management.

In [15], Castro and colleagues describe a forest fire controller based on fuzzy logic and decision-making methods for improving forest fire detection and prevention. Several environmental indicators, such as gases and oxygen, are measured in real-time in the proposal in order to evaluate the risk factors connected with forest fires in the near term and detect the current prevalence of fire outbreaks throughout diverse forest areas. The analytical hierarchy process approach is used to determine the level of fire spread and subsequently to issue relevant environmental warnings via a mobile app. Niranjan *et al.,* [26] developed an IoT-based gadget with incorporated automatic characteristics to identify the presence of a forest fire as early as possible and to take appropriate action before it spreads over a vast area. Sowah at el.,[38] proposed a sub-system of a multi-sensor-based fire control module in autos that uses neuro-fuzzy logic. The initial fuzzy readings in this system are ambient temperature, smoke density, and flame intensity/distance. The system then uses the neuro-fuzzy approach to predict the chance of a fire happening in automobiles, after which it sends an alarm and notification message to the vehicle's owner. In this scenario, the fire detection subsystem performed 95% of the time in places classified with the neuro-fuzzy system.

Kevin *et al.*, demonstrated the use of fuzzy logic to avoid structure fires in urban buildings utilizing mobile devices and IoT technology in [34]. The system is backed by a monitoring process via a fuzzy inference system, whose heuristic model alters the ambient parameters acquired by electronic sensors and transmits the generated information to citizens' mobile devices. Sowah et al. [14] proposed a designed hardware device that detects flames early on and significantly aids to firefighting operations. The authors used multi-sensors to detect the presence of smoke, temperature fluctuations, and flame, and then used a fuzzy logic system to determine the fire situation. However, unlike the latter for efficient fire detection, the proposed approach takes into account a variety of input characteristics such as temperature, humidity, gas combustion, and flame to assess the level of risk.

Sahu *et al.*, [39] suggest utilizing fuzzy logic and a generic algorithm to develop an integrated intelligent system for IoT device selection and placement in opportunistic networks. The system operates as follows: i. The node reads the building parameters from the fire WSN, ii. It operates on the building's fire alarm, iii. It processes the collected data and finds abnormal by the algorithm related, iv. The node displays the read data and results, v. The system makes an appropriate response mechanism based on the results and measurement, vi. The system functions and communicates with the fire department and the many users, vii. The measurement data obtained by the computer from the sensor node is recorded in the database server on a regular basis for future reference.

Dubey *et al.*, suggested a forest fire detection system based on IoT and Artificial Neural Networks (ANN) in [40]. The proposed early detection concept makes use of Raspberry Pi microcontrollers and the necessary sensors, such as temperature, gas, and flame. Data from these sensors is collected and delivered to the microcontroller. The data is stored and analyzed on a centralized server. For prediction, a feed-forward fully connected neural network is used. The authorities in the vicinity are then notified. Kumar *at el.,[*41] proposed a "Fire Buster" (Automatic Alert System) that emits a loud alert to notify building inhabitants of an impending evacuation. The device may additionally relay data to the fire department via IoT sensors. When a fire detector detects a fire-related incident, data is forwarded to the central station. The suggested system has fewer hardware components and interconnections. As a result, the cost is reduced while also making use of code reusability.

2.6 Limitations of Fuzzy Logic compared to Machine Learning

The major drawback of fuzzy control systems is their dependence on human knowledge and expertise. So, the rules of the fuzzy-based control system must be regularly updated. Fuzzy logic decisions are uncertain. Whereas machine learning provides model-learning capabilities based on historical date patterns to make better intelligent decisions.

2.6.1 Summarized Discussion of Related Works, Proposed Solution and Limitations

Related Works	Proposed Solution	Limitations
Sarwar et al. [85]	Presents ANFIS for fire detection and provide a warning. The fire monitoring application system is used in smart buildings and notifications are send via GSM, giving an accuracy of 95%	Using ANFIS yields better results than Type-1. However, the IT2 TSK outperforms the ANFIS system technique yields a better outcome.
Surya Devi et al. [42]	Devi et al., presented a fuzzy–based smart fire detection system. Uses DHT11, and MQ2 sensors to detect fire and	However, Type-1 systems are highly susceptible to inherent error uncertainties, which decrease the performance of

	sends a notification via WhatsApp and the web interface.	the desired outcome. Hence, this means less accuracy compared to type-2 fuzzy based systems design.
Pacori et al. [83]	Presents fuzzy failure detection in transformers using dissolved gas analysis, giving an accuracy of 91%.	However, the authors used a Type-1 fuzzy system with a higher error bound, giving it less accuracy.
Rafiq et al. [24]	Presented a fire extinguisher robot based on fuzzy logic to put out a fire in a room. The robot identifies a room with fire and extinguishes it by mapping out the room, the solution is simulated using MATLAB.	However, using a Type-1 fuzzy system to obtain the position of a room with fire, some errors were established in identifying the actual position of the room using MATLAB.
Listyorini et al. [31,41]	Presents a solution of IoT and fuzzy logic to detect fires in Indonesia using flame, temperature, servo motors, buzzers, and cameras controlled by the ESP8266 and fuzzy logic to analyze flame intensity.	However, the Type-1 solution presented did not consider fire intensity detection on the dissipated combustion gases and also gave less accurate results.
Li et al. [93]	Proposed an image–based fire detection using CNN for providing alerts and early warnings. A precision value of 83.7% was achieved	However, unlike fuzzy control systems large datasets are needed for effective fire detection to function.

2.7 Conclusion

Fire disasters cause ecological, social, and economic damage if not appropriately mitigated and controlled. Therefore, there is a need to deploy early warning systems to safeguard and minimize loss of life and property within the community due to rampant fire outbreaks in local markets in East Africa (EA). Hence, early, precise fire detection and autonomous response are critical and beneficial to disaster management systems. Related works cited several techniques for fire detection and monitoring amid others i.e., satellite systems and optical digital sensors with cameras, which are highly expensive for developing nations to acquire and are a major limitation for developing nations. However, the use of satellite technology has long scanning cycles, which continuously cause long delays for fire to be detected. However, the use of wireless sensor network (WSN) technology has been proven to be the most effective of all due to its robustness, low maintenance, low cost, accuracy, high scalability, and ease of deployment. The integration of sensor-based technology supported by the IoT enhances the concept of smart fire monitoring and accurate detection. Real-time datasets were collected, modeled, and analyzed in order to obtain an accurate fire intensity value prediction based on the fuzzy logic technique. This subsequently supports an appropriate, effective, timely, and informed decision relevant to future fire disaster management, containment, and control. Future works intends to use more appropriate technologies such as machine learning to provide better informed intelligent decisions.

CHAPTER 3

IoT-BASED FUZZY DETECTION MODEL FOR EARLY FIRE DETECTION AIDING SAFETY AND CONTROL IN THE LOCAL URBAN MARKETS

Chapter 3 was developed based on the following article: "E. Lule, C. Mikeka, A. Ngenzi, and D. Mukanyiligira, "Design of an IoT-Based Fuzzy Approximation Prediction Model for Early Fire Detection to Aid Public Safety and Control in the Local Urban Markets," Symmetry, vol. 12, no. 9, p. 1391, Aug. 2020, doi: 10.3390/sym12091391"

3.1 Introduction.

According to recent technological breakthroughs in the Internet of Things (IoT), over 50 billion gadgets shall be connected to the internet by 2050[33][40]. Hence, the development of WSN-IoT-based systems gives reliable information about the fire situation on the ground to the fire and rescue department. Fire disasters necessitate more accurate and efficient fire prediction models in order to improve monitoring [42][43]. Therefore, we seek to develop an accurate fire detection model based on the notion of fuzzy logic approximation. In this research study, the proposed fire detection model is employed as a foundation for the design and implementation of future fuzzy-based fire detection systems, assisting public protection and safety in the local urban markets of East African (EA) [2][1].

In Fig. 3.1, we graphically represent the percentage (%) frequencies of fire occurrences for the selected local urban markets within the (EA) region, namely Owino, Uganda, Gikomba, Kenya, and Nyanza or Gisozi, Rwanda, throughout a 10-year period from 2009 to 2019.

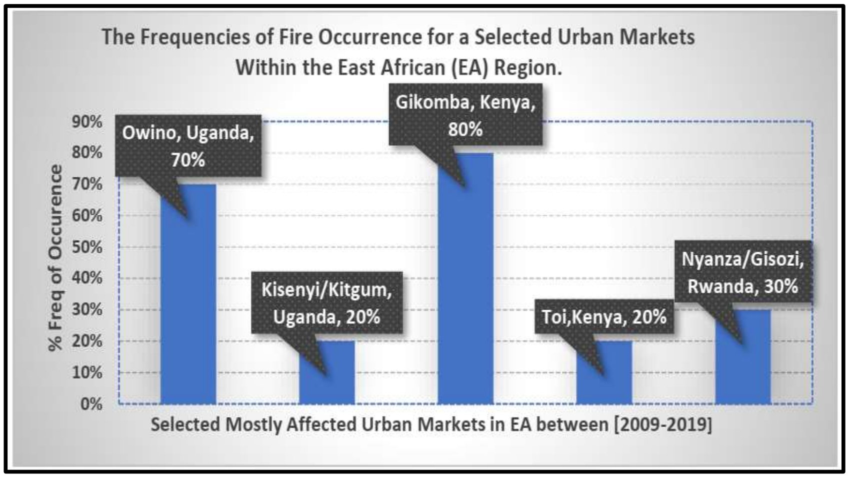


Fig. 3.1: Representation of (%) Frequencies of Fire Occurrences in Selected Urban Markets within the East Africa (EA) Region Between (2009–2019)[3][4].

3.2 Fuzzy Approximation Modeling.

3.2.1 Overview Concept of Fuzzy Logic

Fuzzy logic is a soft computing technique based on the idea of degrees of truth ranging from 0 to 1, inclusive. As a result, fuzzy sets have a crisp value [x] and a membership value [μ] in the range [0,1]. In this study, we used a fuzzy approximation modeling technique to develop a fuzzy detection model that aids in early fire detection within the (EA) local market community [44][45].

Fuzzy logic aids us in modeling dynamic nonlinear real-time systems with complicated computational engineering challenges that have imprecise or incomplete datasets [46][47]. As a result, the proposed approach is used to estimate the percentage Fire Intensity (FI) for a particular "fire status" using fuzzy approximation reasoning. To completely understand the dynamic performance behavior of the suggested detection model design, simulation and modeling methods were performed in MATLAB Fuzzy Logic Toolbox.

3.2.2 Stages of Fuzzy Control Model Design

The fuzzy control model was developed to approximate fire intensity and then determine the probability of fire occurrence in order to make an informed decision. The design of a fuzzy approximation model is divided into stages, which are as follows; *model fuzzification*, *model fuzzy rules, model inference engine* and *model defuzzification and evaluation* as discussed in the Fig. 3.2. Below;

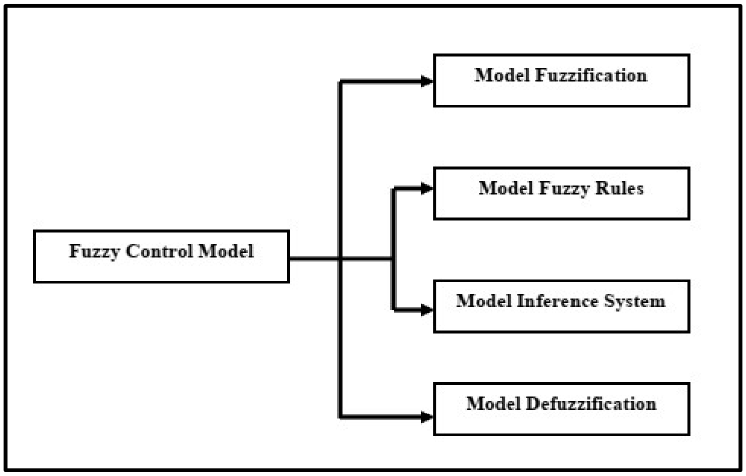


Fig. 3.2. The Major Principal Design Stages of the Proposed Fuzzy Detection Control Model [34][35].

i) Model Fuzzification

The fuzzy control detection model for early fire detection, six multisensory input crisp parameters and their corresponding fuzzy membership values, are defined; i) temperature change (ΔT) = {very low, low, medium, high, very high}; ii) humidity (ΔH) = {dry, optimal, moist}; iii) carbon monoxide (ΔCO) = {low, medium, high}; iv) carbon dioxide (ΔCO_2) = {low, medium, high}; v) oxygen (ΔO_2) = {low, medium, high}; vi) the flame presence = {"true" or "false"}. We intended to minimize the potential risks of false alarms that may be generated. We considered three combustion gases for an efficient fire detection i.e., CO_2, CO and O_2. Because, all combustible materials contain a carbon element supporting burning. This element, supported by O_2 supports fire combustion, giving CO and CO_2. This results in a drop in O_2 levels in the surrounding area and a subsequent decrease in the fire intensity (FI) of the burning flame. The FI, output of heat generated per unit time. Also called, Estimated Fire Intensity Prediction (EFIP) as the fuzzy output with membership values: {very low, low, moderate, high, very high}. In the study, three member functions (MF) are utilized for effective fire detection based on fuzzy modeling using MATLAB: triangular (trimf) MF, the Gaussian (gauss) MF, and, the trapezoidal (trapmf) MF.

ii) Model Fuzzy Rules

Using the Fuzzy Associative Memory (FAM) method, different associative transforms map input values to equivalent output fuzzy sets are generated to form a FAM matrix of inference rules used to design the fuzzy detection model [36]. This research study utilizes a combination of both square and cube FAM methods to generate the required inference rules, as detailed in Tables 3.1 and 3.2, which are applied to the proposed fuzzy model. The model subsequently aids in early fire detection in urban markets for purposes of public safety and control. FAM methods are widely accepted to model and optimize fuzzy systems. This effectively improves the performance of the captured content associations Forty-two (42) inference rules, i.e.: {27 + 15}: {27 = 3 × 3 × 3 × 1; 15 = 3 × 5 × 1}, were generated for the fuzzy based model as[2]:

Table 3.1: FIS rules for Initial Environmental Parameters

Rule No̲.	Temperature (^{0}C) (ΔT)	Humidity (%) (ΔH)	Estimated Fire Intensity Prediction (EFIP) (%)
1.	Very Low	Dry	**L**
2.	Very Low	Optimal	**L**
3.	Very Low	Moist	**L**
4.	Low	Dry	**L**
5.	Low	Optimal	**L**
6.	Low	Moist	**L**
7.	Medium	Dry	**M**
8.	Medium	Optimal	**M**
9.	Medium	Moist	**L**
10.	High	Dry	**H**
11.	High	Optimal	**H**
12.	High	Moist	**L**
13.	Very High	Dry	**H**
14.	Very High	Optimal	**H**
15.	Very High	Moist	**L**

Table 3.2: FIS rules for Gases Combustion

Rule No̲.	Smoke Intensity (ΔCO) (ppmv)	Carbon dioxide (ΔCO_2) (ppmv)	Oxygen Level (ΔO_2) (ppmv)	Estimated Fire Intensity Prediction (EFIP) (%)
1.	Low	Low	Low	**L**
2.	Low	Medium	Low	**M**
3.	Low	High	Low	**H**
4.	Medium	Low	Low	**H**
5.	Medium	Medium	Low	**VH**
6.	Medium	High	Low	**VH**
7.	High	Low	Low	**VH**
8.	High	Medium	Low	**VH**
9.	High	High	Low	**VH**
10.	Low	Low	Medium	**VL**
11.	Low	Medium	Medium	**M**
12.	Low	High	Medium	**M**
13.	Medium	Low	Medium	**M**
14.	Medium	Medium	Medium	**H**
15.	Medium	High	Medium	**L**
16.	High	Low	Medium	**M**
17.	High	Medium	Medium	**H**
18.	High	High	Medium	**L**
19.	Low	Low	High	**VL**
20.	Low	Medium	High	**VL**
21.	Low	High	High	**H**
22.	Medium	Low	High	**VL**
23.	Medium	Medium	High	**L**
24.	Medium	High	High	**L**
25.	High	Low	High	**L**
26.	High	Medium	High	**L**
27.	High	High	High	**L**

iii) Model Fuzzy Inference Systems

This is the key logical system component of the fuzzy control systems that is responsible for effective decision making. It is composed of IF…THEN structure connectors i.e., “OR” and “AND”. Mathematically, AND, OR operators are defined in Eqn. (3.1) and (3.2) respectively;

$$\mu(Q \cap Y) = \min\,[\mu Q(x), \mu Y(x)] \qquad (3.1)$$

$$\mu(Q \cup Y) = \max\,[\mu Q(x), \mu Y(x)] \qquad (3.2)$$

where μQ; membership function in Class A, μY; membership function in Class B.

In the study, we used the “AND” operator to determine the minimum probability of a fire outbreak occurrence [48]. We applied the Mamdani FIS to design the proposed fuzzy model because of its widely acceptable and provide reasonably good results compared to the Takagi, Sugeno, Tangi (TSK) FIS [37][38][39]. So, the FIS is used to determine the appropriate decision making of a prevailing fire status. Using the Mamdani method, we were able to generated corresponding fuzzy control rules defined in Table 3.1 and 3.2 above.

iv) Model Defuzzification and Evaluation

Defuzzification is an inverse transformation process mapping fuzzy outputs from the fuzzy domain back into the crisp output domain [40][41]. In this research approach, we use centroid defuzzification or Center of Gravity (CoG). The CoG, is widely acceptable method because the output defuzzification values tend to move smoothly in the fuzzy region, giving a more accurate and precise representation. Mathematically, CoG is defined as;

$$(\text{EFIP}) = \text{Crisp Output: } \mu(\mho) = \{\Sigma\mu Q\,(\mho)\,.\,\frac{\mho}{\Sigma\mu Q\,(\mho)}\} \qquad (3.3)$$

This evaluates to a single crisp value $\mu Q\,(\mho)$, and $\mho$ center of the membership function.

3.2.3 Architectural Design Overview of Fire Detection Model

Fig. 3.3 shows a typical architectural overview of the fire detection model through interacting with its corresponding components. Several sensor components, such as DHT22, which records temperature and humidity changes; UR/IR, which detects the presence of flame; and MQ5, which detects the presence of a gas, are used. These sensor components are used to detect any abnormal environmental changes noticeable due to the presence of a fire outbreak. Sensor data is then gathered and transmitted to the microcontroller unit (MCU) for further processing. The collected data is then transmitted to the cloud API. Fuzzy inference rules are then applied to the data using an appropriate fuzzy detection algorithm to obtain an informed decision of the fire status, i.e., the Estimated Fire Intensity Prediction (EFIP) (%). The algorithm was then developed and tested using the Arduino (IDE) platform. In order to simulate the model, the MATLAB Fuzzy Toolbox was used[42]. The obtained results are analyzed to fully understand the performance of the model based on the fuzzy inference rules.

3.2.4 Architectural Overview Design of the Proposed Fire Detection Model.

The model architecture is made up of input sensors DHT 22 for temperature and humidity, MQ5 for CO2 and CO detection, and Flame sensors for data collecting. Inference rules are applied to the collected data for analytical purposes using a microcontroller (MCU), and an appropriate decision is determined based on the state of fire.

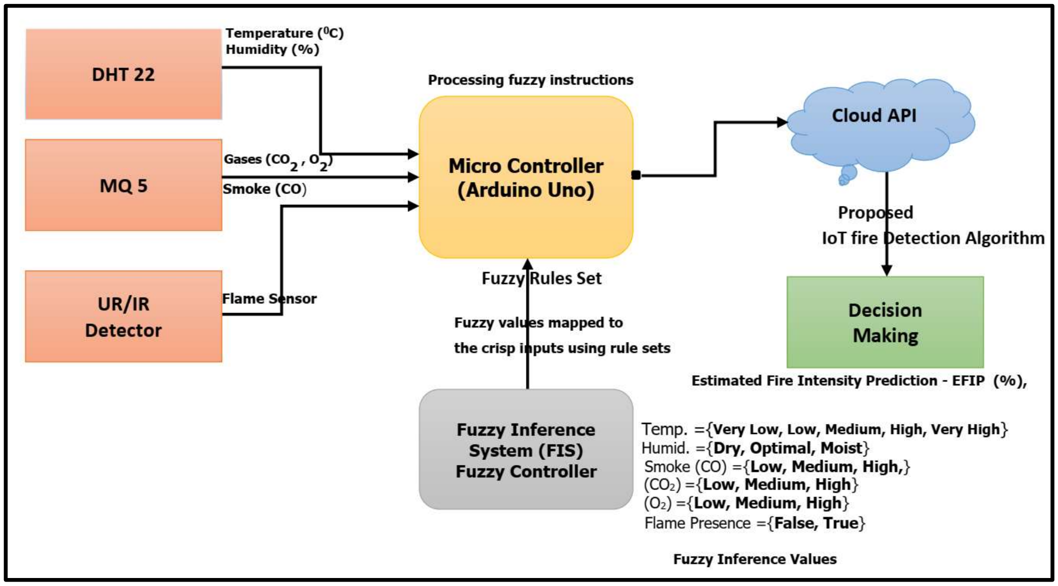


Fig. 3.3: Architectural Overview of the Proposed Fuzzy-Based Fire Control Model.

3.2.5 Simulation Parameters Considered.

In Tables 3.3 and 3.4, several simulation input and output parameters are considered to evaluate the performance behavior of the proposed model using the MATLAB Fuzzy Logic Toolbox environment.

Crisp Input Variable.	Fuzzy Input Parameters.	Fuzzy Domain Range.	Universe of Discourse for MFs
Temperature(ΔT)	Very Low, Low, Medium, High, Very High.	**[0-100]**	**0-20**, **20-40**,**40-60**, **60-80** and **80-100** respectively.
Humidity (ΔH)	Dry, Optimal, Moist.	**[0-100]**- (%)	**0-40**, **40-80**, **80-100**
Smoke Intensity (CO)	Low, Medium, High.	**[0-100]**	**0-40**, **40-80**, **80-100**
Carbon dioxide (CO_2)	Low, Medium, High.	**[0-100]**	**0-40**, **40-80**, **80-100**
Oxygen Level(O_2)	Low, Medium, High.	**[0-100]**	**0-40**, **40-80**, **80-100**
Flame Presence	Boolean: False, True.	[False, True]	**0**, **1**

Table 3.3: The Crisp and Fuzzy-Based Input Parameters, Domain Ranges, and Universe of Discourse Membership Function.

Crisp Output Variable.	Fuzzy Output Parameters	Fuzzy Domain Range.	Universe of Discourse for MFs
Estimated Fire Intensity Prediction (EFIP) %	Very Low, Low Moderate, High, Very High.	[**0-100**]- (%)	**0-20**, **20-40**, **40-60**, **60-80** and **80-100** respectively.

Table 3.4: The Crisp, Fuzzy Based Output Parameters, Domain, Universe of Discourse Membership Function**.**

3.3 Simulation Lab. Experiment Setup.

3.3.1 Fuzzy Control Systems (FCS) Design

In sect. 3.3.1, we show the stepwise design and simulation of the fuzzy fire detection model using the MATLAB Fuzzy Toolbox. Using Mamdani FIS integrated within MATLAB, several observations are noticeable. Fig. 3.4 illustrates the design of initial changes in temperature and humidity due to a flame's presence vis-à-vis the EFIP. Also, Fig. 3.5 represents the gases, i.e., CO_2, CO, and O_2, that are dissipated due to fire combustion and their effect on EFIP[2].

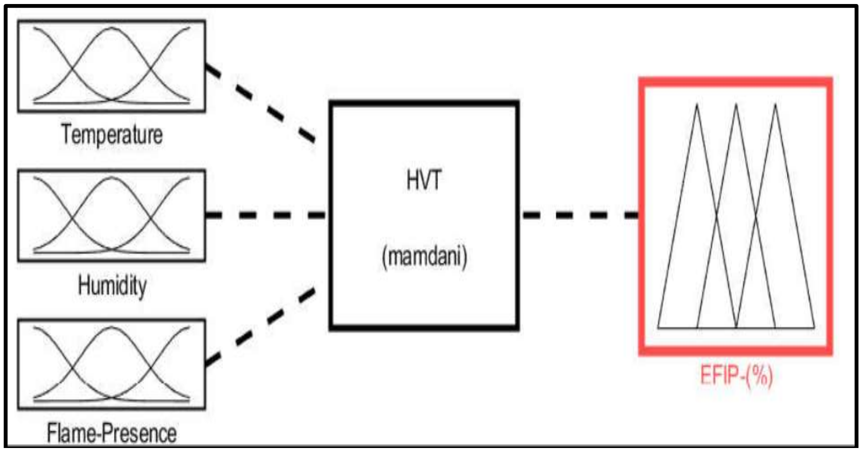


Fig. 3.4. Design of the fuzzy control system (FCS) model for Temperature, Humidity and Flame Presence vs EFIP (%).

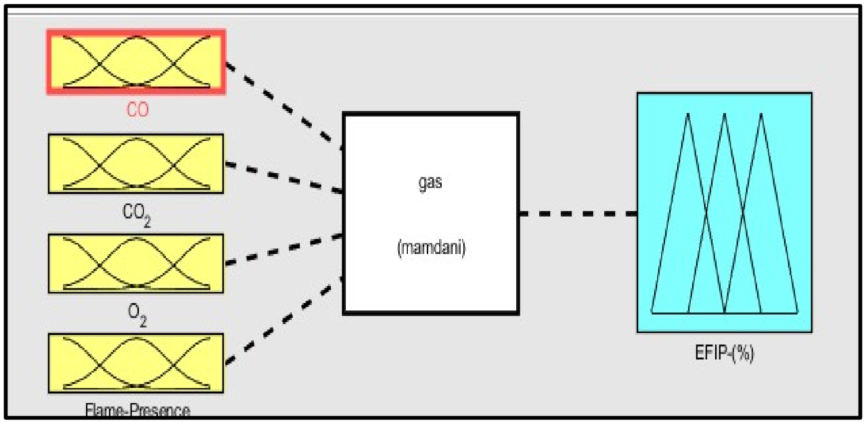
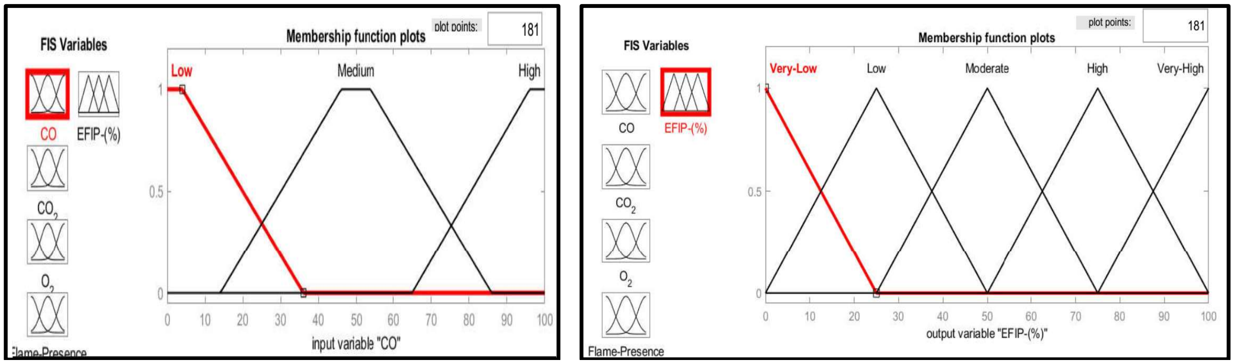


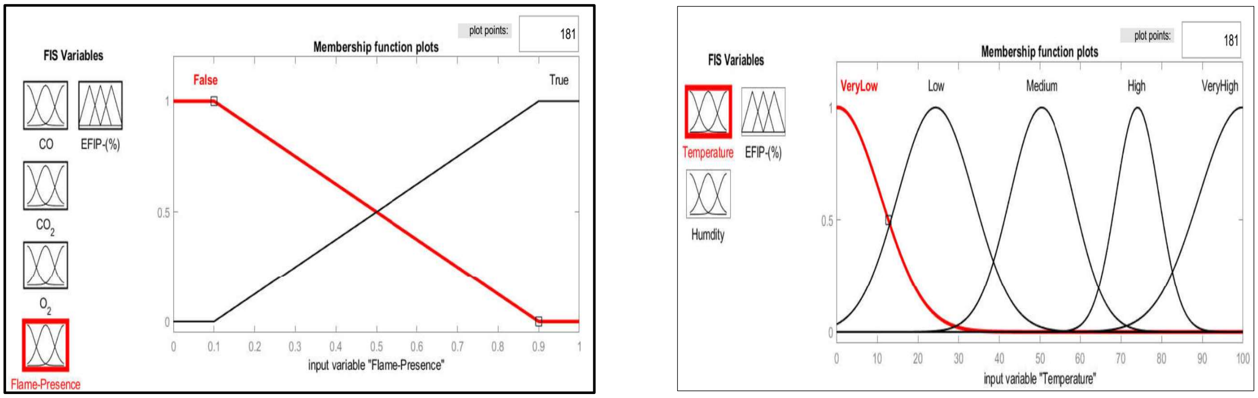
Fig. 3.5. Design of the FCS model for gas combustion, i.e., CO, CO_2, O_2 and Flame Presence, vs EFIP (%)[2].

3.3.2 Input/Output Fuzzy Membership Functions Designs

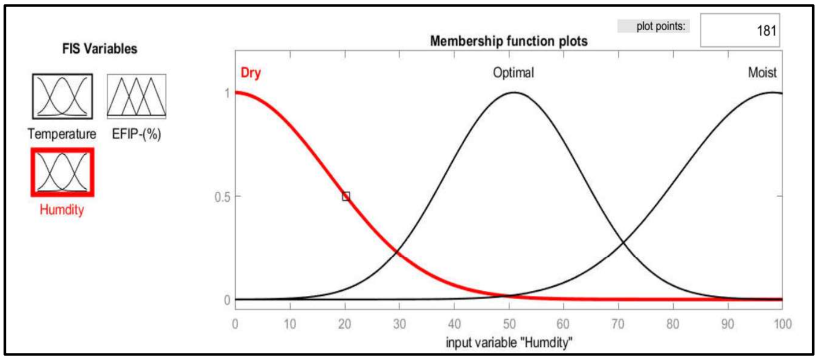
The sample designs of the input/output for the proposed fuzzy inference systems (FIS) variables with associated membership function plots are shown in Fig. 3.6a-e. For example, in Fig. 3.6a, the FIS input variables for CO are {low, medium, and high}, while humidity has the membership functions {dry, optimum, and wet}. Similarly, the EFIP is a FIS output variable represented by the following values: {very low, low, moderate, high, very high}.



(a): Carbon monoxide (CO) (b):Estimated Fire Intensity Prediction (EFIP)



(c): Flame Presence (d):Temperature

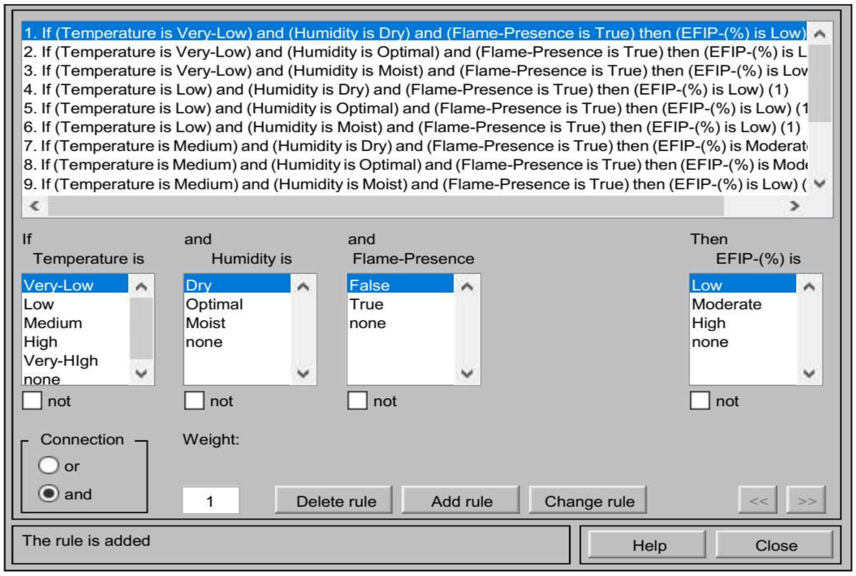


(e): Humidity

Fig. 3.6 (a-e): Membership Function Design Plots for the Different Fuzzy Inference System (FIS) Representing Input/Output Variables [2].

3.3.3 MATLAB Evaluation Rules Editor for the Proposed Fuzzy Control Model

In Sect. 3.3.3, we show the proposed fuzzy inference rules design in the MATLAB rules view window, Fig. 3.7(a-b), that are used to evaluate the fuzzy approximation model. The "AND" operator is mainly used in the design and simulation of the fuzzy approximation model. Because of its significance in determining the minimum probability of the EFIP of a given fire status, given its fuzzy inputs. We consider an equal-weight priority function (W = 1). Implying that the evaluation rules have equal priority when evaluating the resultant model design. The flame presence is set to "true" for all evaluation rules. This is relevant in minimizing the possibility of a false alarm rate.



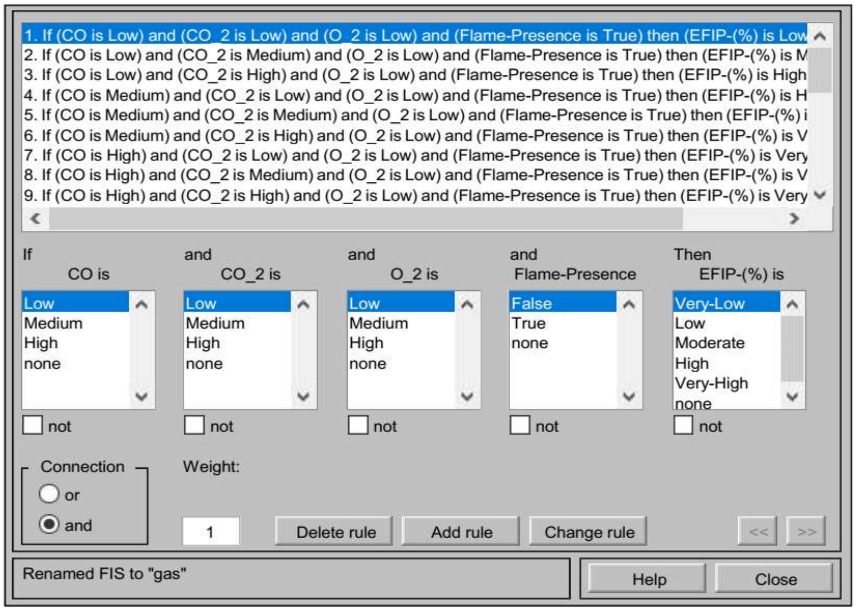
1. If (Temperature is Very-Low) and (Humidity is Dry) and (Flame-Presence is True) then (EFIP-(%) is Low)
2. If (Temperature is Very-Low) and (Humidity is Optimal) and (Flame-Presence is True) then (EFIP-(%) is L
3. If (Temperature is Very-Low) and (Humidity is Moist) and (Flame-Presence is True) then (EFIP-(%) is Lov
4. If (Temperature is Low) and (Humidity is Dry) and (Flame-Presence is True) then (EFIP-(%) is Low) (1)
5. If (Temperature is Low) and (Humidity is Optimal) and (Flame-Presence is True) then (EFIP-(%) is Low) (1
6. If (Temperature is Low) and (Humidity is Moist) and (Flame-Presence is True) then (EFIP-(%) is Low) (1)
7. If (Temperature is Medium) and (Humidity is Dry) and (Flame-Presence is True) then (EFIP-(%) is Moderat
8. If (Temperature is Medium) and (Humidity is Optimal) and (Flame-Presence is True) then (EFIP-(%) is Mod
9. If (Temperature is Medium) and (Humidity is Moist) and (Flame-Presence is True) then (EFIP-(%) is Low) (

Connection: ○ or ● and

Weight: 1

The rule is added

(a) Initial Environmental Parameters: Temperature, Humidity and Flame Presence vs EFIP.



1. If (CO is Low) and (CO_2 is Low) and (O_2 is Low) and (Flame-Presence is True) then (EFIP-(%) is Low
2. If (CO is Low) and (CO_2 is Medium) and (O_2 is Low) and (Flame-Presence is True) then (EFIP-(%) is M
3. If (CO is Low) and (CO_2 is High) and (O_2 is Low) and (Flame-Presence is True) then (EFIP-(%) is High
4. If (CO is Medium) and (CO_2 is Low) and (O_2 is Low) and (Flame-Presence is True) then (EFIP-(%) is H
5. If (CO is Medium) and (CO_2 is Medium) and (O_2 is Low) and (Flame-Presence is True) then (EFIP-(%) i
6. If (CO is Medium) and (CO_2 is High) and (O_2 is Low) and (Flame-Presence is True) then (EFIP-(%) is V
7. If (CO is High) and (CO_2 is Low) and (O_2 is Low) and (Flame-Presence is True) then (EFIP-(%) is Very
8. If (CO is High) and (CO_2 is Medium) and (O_2 is Low) and (Flame-Presence is True) then (EFIP-(%) is V
9. If (CO is High) and (CO_2 is High) and (O_2 is Low) and (Flame-Presence is True) then (EFIP-(%) is Very

Connection: ○ or ● and

Weight: 1

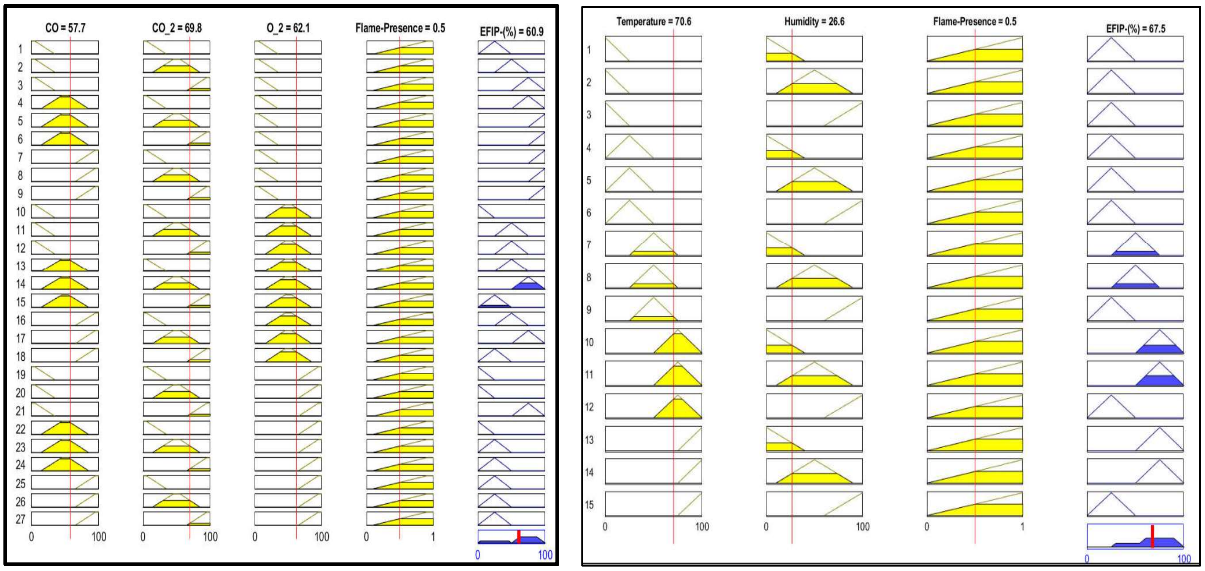
Renamed FIS to "gas"

(b) Gas combustion, i.e., CO, CO_2, O2, and Flame Presence vs EFIP.

Fig. 3.7 (a-b): MATLAB Evaluation Inference Rules Editor View Design for Various Input/Output Parameters

3.4. MATLAB Evaluation Rules Viewer

Fig. 3.8a, shows the rule view insights of the effect on the EFIP due to gas combustion and then Fig.3.8b, the initial impact of temperature and humidity changes due to a fire occurrence. We observe, ref. Fig. 3.8a, that resultant fire gas combustion and the corresponding effect on EFIP (%). For instance, if CO = 57.7 ppmv, CO_2 = 69.8 ppmv, O_2 = 62.1 ppmv, flame presence = 0.5, then the EFIP = 60.9% under the above fire conditions. Likewise, Fig. 3.8b, illustrates that the result rule view of the above experiment yielded to the following; Temperature = 70.6 °C, humidity = 26.6%, flame = 0.5 vs EFIP = 67.5%.



(a) CO, CO_2, O_2, flame vs EFIP. **(b)** Temperature, humidity, flame vs EFIP

Fig. 3.8(a-b): Determination of the probability of (EFIP) using the MATLAB2018a rule view[2].

3.5. Results and Discussions

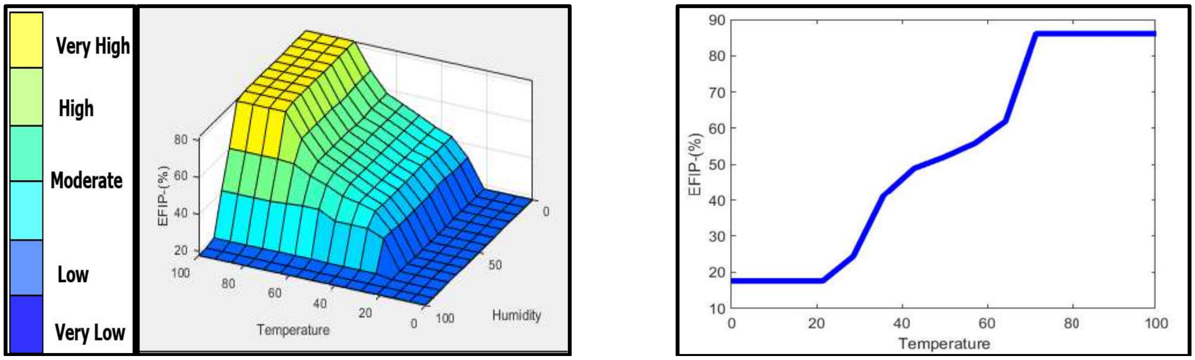
After careful modeling and simulation of the fuzzy approximation control model, Insights from the obtained results are observed. A comparative study of the performance between the considered environmental parameters and the EFIP is made for an effective and informed decision reflecting the prevailing fire status.

3.5.1. Initial Environmental Parameters, i.e., Temperature, Humidity and Flame Vs Estimated Fire Intensity Prediction (EFIP)

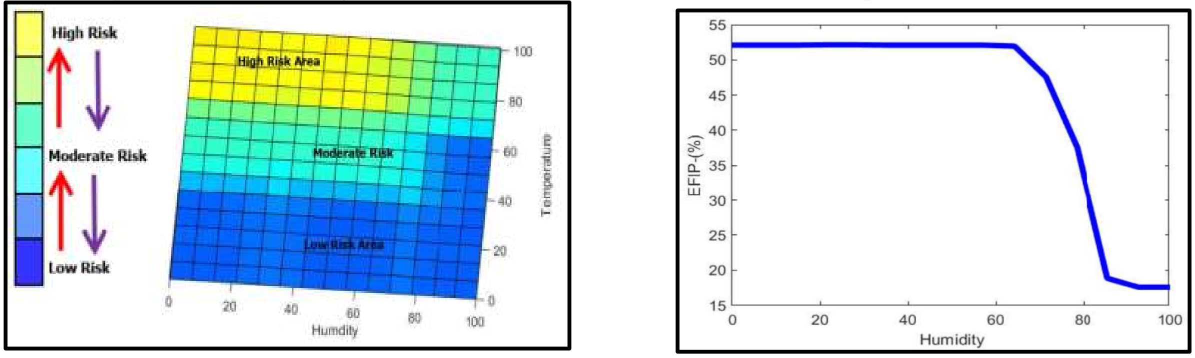
Fig. 3.9(a–e) illustrates the comparative performance of the suggested parameters for the model design, namely, rate of change of temperature and rate of change of humidity, vis-à-vis the output parameter, estimated fire intensity prediction (EFIP). EFIP is determined as the percentage of true fire incidence with respect to input variables. Recall that Fig. 3.9b, d represents a 2D view of Fig. 3.9a. In the initial stages of a fire outbreak, we realize that lower temperatures yield high humidity conditions, resulting in a lower EFIP, or fire intensity. We also observe that temperatures significantly increase with increased EFIP (cf. Fig. 3.9b). Lower temperatures are due to a high moisture content in the atmosphere, lowering the EFIP. Also, a gradual increase in temperature decreases the humidity conditions until the dryness conditions are reached, subsequently lowering the EFIP (cf. Fig. 3.9d). Fig. 3.9c, represents a lower risk level experienced, i.e., the "blue" region. Hence, a further increase in temperature migrates the risk factor to the moderate level and subsequently higher risk levels, represented by the "yellow", region in Fig. 3.9c. Averagely low temperatures are experienced with an increase in moisture content, which lowers the EFIP and vice versa.

During the initial stages of a fire outbreak (cf. Fig. 3.6b), say with an EFIP < 20% and a temperature = 20 °C, high moisture content is yielded, lowering the EFIP. This is due to high humidity conditions being present. However, increased temperatures beyond 20 °C increase the EFIP. The EFIP further increases with increased temperatures, as observed in Fig. 3.9b. It should be noted that, high temperatures subsequently result in lower humidity conditions, hence an increased EFIP.

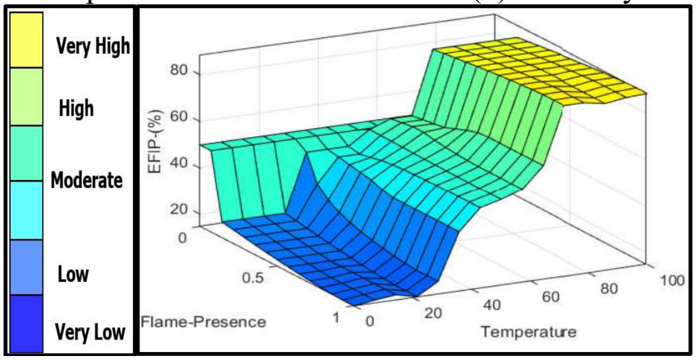
Secondly, lower temperatures lead to high humidity conditions, hence decreasing the EFIP. For instance, in Fig. 3.9b, at EFIP = 88% and temperature = 72 °C, it is observed that the EFIP remains constant with increased temperature change for a given period of time due to oxygen being depleted. So, the effect of increased temperatures translates into lower dry humidity conditions for a given environmental setting. In Fig. 3.9d, we observe lower humidity conditions with increasing temperatures, translating into a higher EFIP. Beyond Humidity = 68%, a gradual decrease in EFIP is observed. Because of the increased humidity conditions within the atmosphere, subsequently lowering the temperatures and EFIP. Hence This affects the fire status. Fig. 3.9e shows that a lower temperature significantly yields a lower flame, hence a lower fire intensity. Likewise, higher temperatures may significantly result in a higher EFIP.



(a)Temperature, Humidity **Vs** EFIP (**%**) (b) Temperature **vs** EFIP (**%**)



(c) Humidity vs Temperature (d) Humidity vs EFIP (%)



(e)Temperature, flame presence vs EFIP (%).

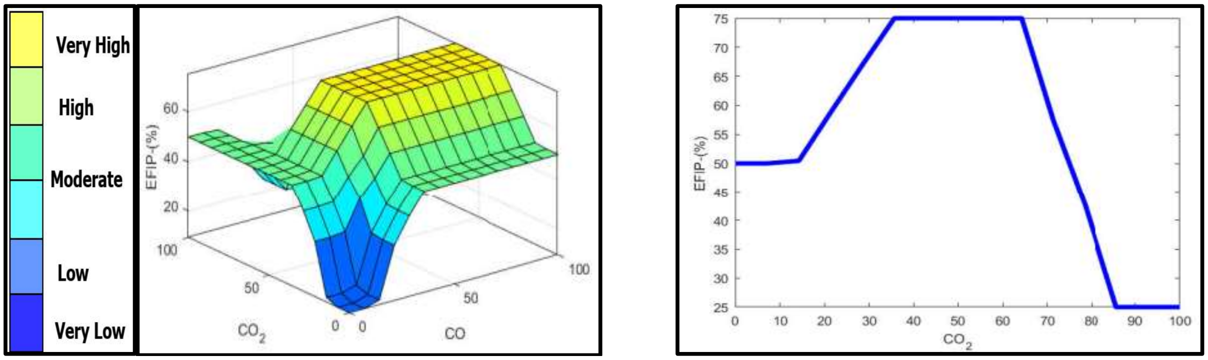
*Key: EFIP (%)■ Very Low, ■ Low, ■ Moderate, ■ High, ■ Very High

Fig. 3.9 (a-e) : Performance comparison of 3D, 2D surface plot view of various input/output parameter pairs considered[2].

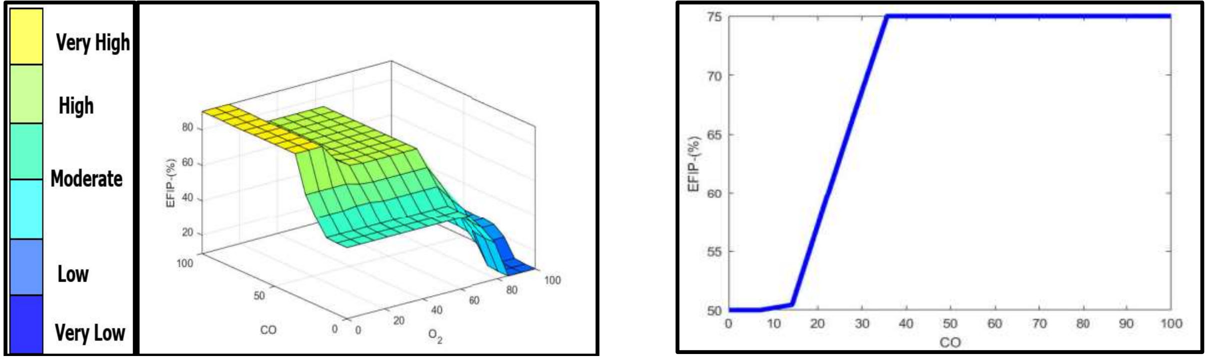
3.5.2. Gas Combustion i.e., CO, CO_2, O_2 and Flame Vs EFIP

In Fig. 3.10(a–e), we observe several comparative insights due to gas combustion, i.e., ΔCO, ΔCO_2 and ΔO_2, vis-à-vis fire intensity (EFIP) arising from a fire outbreak. The results are discussed herein; In Fig. 3.10a, initial lower gas concentration levels of CO and CO_2, which further rises with subsequent increase in EFIP. Fig. 3.10b, at CO_2 = 17 ppmv, EFIP = 50%, there is gradual increase in CO_2 levels due to increased EFIP, until 75%, when the fire intensity then becomes constant ending at CO_2 = 67 ppmv. Beyond 67 ppmv, a sudden drop in the fire intensity (EFIP) observed due to decreased levels of O_2 which supports fire combustion. This finally results into a decrease in fire intensity (EFIP). Fig. 3.10c, an increase in smoke intensity or carbon monoxide (CO) dissipated lowers also the volume of O_2 levels in the surrounding and hence, subsequent increases in fire intensity or (EFIP). The percentage (%) EFIP is computed, using the Eqn. (3.3).

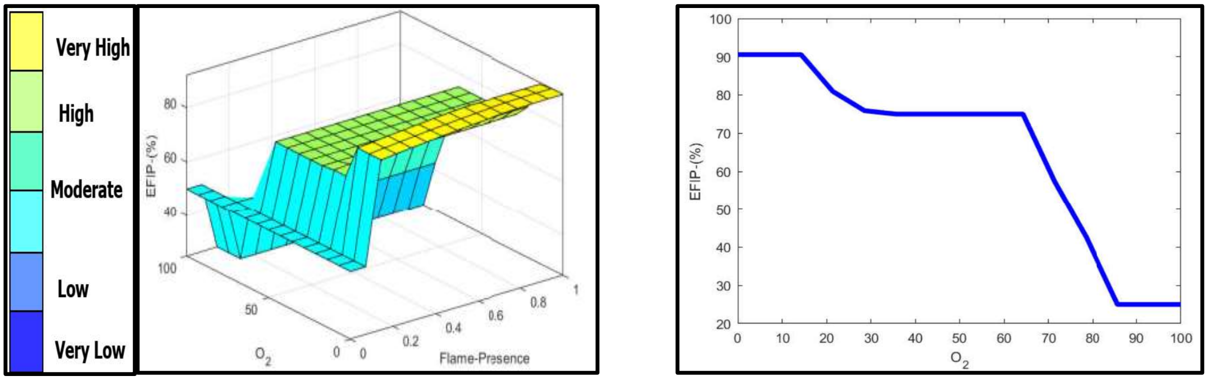
Fig. 3.10f, shows an increased consumption of O_2, lowers the EFIP, as more O_2 is being consumed. Hence, this results into an increase the fire intensity. However, O_2 levels gradually reduce with time. This eventually translates into lower fire intensity (EFIP). Additionally, as more O_2 levels are reduced by the burning flame, this increases the CO_2 levels dissipated. Hence, a drop in the fire intensity (EFIP). Because CO_2 does not support the combustion as noted In Fig. 3.10b. Decreased O_2 levels are due to support of fire combustion. This further leads to a high dissipation of both CO_2 or CO hence, higher EFIP is realized, ref. Fig. 3.10a. In Fig. 3.10e, increased flame intensity subsequently increases the EFIP as more O_2 is consumed by the burning flame. In Fig. 3.10f, it is noted that, lower levels of O_2, significantly increase the EFIP and vice versa; while higher O_2 levels yielded to lower EFIP, as per the model design.



(a) CO_2, CO vs EFIP (%) (b) CO_2 vs EFIP (%)



(c) CO, O_2 **vs** EFIP (%) (d) CO **vs** EFIP (%)



(**e**) O_2, Flame Presence **vs** EFIP (%) (f) O_2 **vs** EFIP (%)

*Key: EFIP (%)🟦 Very Low, 🟦 Low, 🟦 Moderate, 🟩 High, 🟨 Very High

Fig. 3.10 (a-f): Performance comparison of 3D and 2D surface plot view of various input/output parameter pairs considered[2].

3.6 Obtained Experimental Data Results.

In Table 3.5, we study the comparative performance of temperature change (ΔT) and humidity change (ΔH) vis-à-vis the EFIP for 12 sampled rule outcomes of the experiment. In Fig. 3.11, we show the resultant graphical comparison of the data output generated in Table 3.5. We observe that, at lower temperatures, there are high humidity conditions, hence a lower EFIP (refer to the dotted line in Fig. 3.11). Likewise, an increase in temperature significantly lowers the humidity conditions towards dryness.

Table 3.5: Temperature Change Vs Humidity Data.

Rule No.	$\Delta T(^0C)$	ΔH (%)	EFIP (%)
1.	9.0	17.5	17.6
2.	15.1	27.1	18.3
3.	38.0	58.4	43.6
4.	50.0	50.0	52.1
5.	28.3	38.0	22.9
6.	40.4	44.0	46.2
7.	46.4	48.8	52.1
8.	52.4	65.7	51.9
9.	62.9	71.7	54.5
10.	66.9	80.1	37.9
11.	68.1	52.4	71.2
12.	68.1	22.3	69.7

Table 3.6: Dissipated Gases Combustion Data.

Rule No.	ΔCO	ΔCO_2	ΔO_2	EFIP (%)
1.	23.6	21.4	23.6	47.8
2.	32.4	29.1	28.0	63.2
3.	36.8	30.2	31.1	69.1
4.	44.5	32.4	39.0	71.3
5.	50.0	37.9	44.5	75.0
6.	19.2	48.9	51.1	56.5
7.	13.7	8.2	13.7	25.0
8.	64.3	50.0	17.0	86.5
9.	70.9	24.7	32.4	62.8
10.	32.4	46.7	65.4	70.3
11.	48.9	75.3	86.3	25.0
12.	57.7	69.8	62.1	60.9

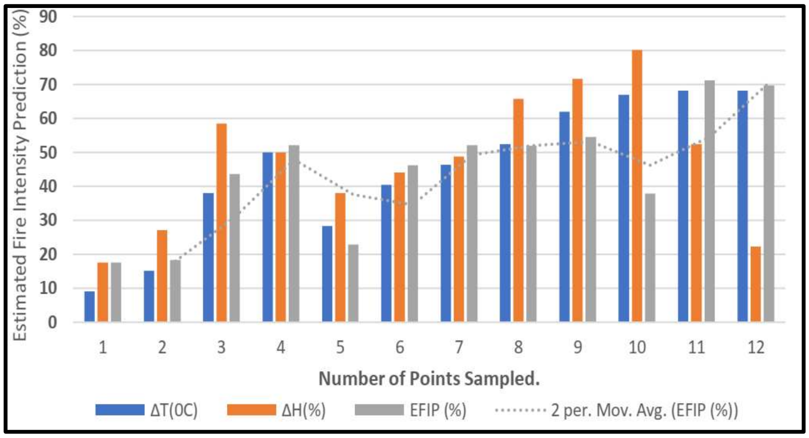


Fig. 3.11: Performance comparison of temperature and Humidity vs EFIP for 12 sampled data points [2].

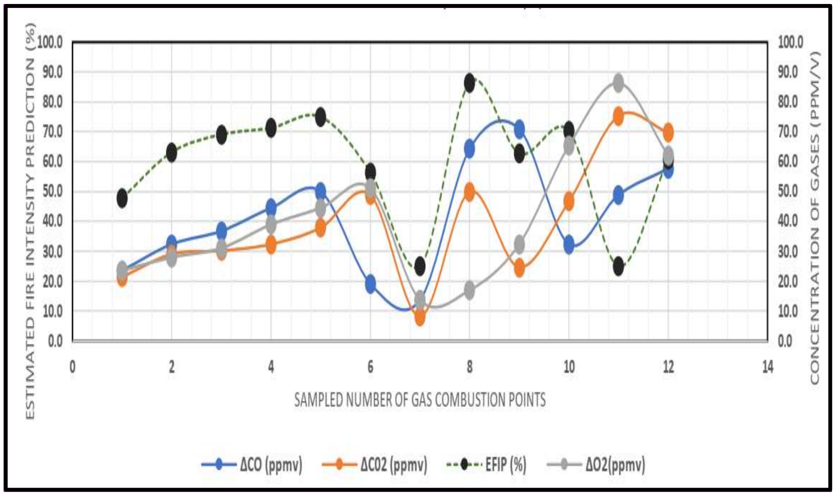


Fig. 3.12: A Performance comparison of CO, CO_2 and O_2 vs EFIP for 12 sampled data points [52].

From the experiment above, it was noted that excessively high temperatures tend to vaporize the humidity conditions thereby increasing the EFIP. This phenomenon is realized at sampled data points 11–12, of Fig. 3.11. Hence, the latter figure illustrates the behavior of the EFIP, say, from very low at point 1, to very high EFIP when temperatures are very high, and the humidity conditions decrease to dryness, as observed at point 12. Moderate EFIP is observed at sample points 6–7, where the temperatures and humidity conditions are approximately in equilibrium with the prevailing conditions.

In Table 3.6, we observe the behavior of gases dissipated, i.e., (ΔCO), and (ΔCO_2), due to fire outbreak combustion in support of (ΔO_2) levels. In Fig. 3.12, we, observe that lower levels of CO_2 or CO yield into lower EFIP. Also, note that lower levels of CO_2 translate a lower temperatures or higher humidity conditions due to a fire outbreak. However, at data points 2–5, there's a relative increase in both CO_2 and CO concentration levels due to increased temperatures. Hence, a higher EFIP is expected, coupled with a lower humidity condition.

3.6.1. Gas Combustion Efficiency (GCE)

The Gas Combustion Efficiency (GCE) is a measure of the heat content generated by the burning fuel flame that is later transferred as usable heat resulting from combustion. Note that temperature, O_2, and CO_2, are the essential elements of combustion efficiency. For all presence of flame = {true} inputs to the fuzzy model and combustion of gases dissipated in the atmosphere are measured in parts per million per volume (ppmv). The combustion efficiency (GCE) is defined by the formula:

$$\text{GCE} = \frac{\Sigma \Delta CO_2}{\Sigma(\Delta CO + \Delta CO_2)} \times 100\% \tag{3.4}$$

where GCE, gas combustion efficiency of the burning fire flame with respect to ΔCO_2, ΔCO and O_2.

From Table 3.6, we calculate the GCE of the gases dissipated for the model as follows. From Eqn. (3.4), the summation of ΔCO, ΔCO_2 can be determined as; $\Sigma(\Delta CO) = 494.4$ ppmv, $\Sigma(\Delta CO_2) = 474.6$ ppmv. From the datasets in Table 3.6, gives a GCE = $(\frac{474.6}{494.7 + 474.6})$ x 100% = 48.96%. Thus the, efficiency of the gases dissipated due to the burning fuel as per the model is 49%. Meaning that, approximately, 50% of the combustion gases, i.e., CO, CO_2, are dissipated with carbon as the primary combustive element. From Table 3.6, we notice that an increase or decrease in the amount of gas dissipated subsequently increases or decreases the EFIP. Thus, an increased efficiency of the burning fuel as clearly indicated by the dotted line curve in Fig. 3.11 of the EFIP.

3.6.2 Performance Evaluation of the Proposed Fuzzy Based Fire Detection Model

In the study, we further evaluated the performance of the fuzzy detection model to determine the percentage accuracy rate using standard evaluation parameters. Using a *two-factor decision authentication method,* we determine the test and the actual values of the model. Then, the percentage accuracy is determined using the fuzzy inference rules, as detailed in Tables 3.7 and 3.8 below.

Expt. No.	$\Delta T(^0C)$	ΔH (%)	Flame Presence	EFIP (%)	Test Model	Actual Model	Determined Accuracy Rate (%)
1.	9.0	17.5	True	17.6	**L**	**VL**	50%
2.	15.1	27.1	True	18.3	**L**	**VL**	50%
3.	38.0	58.4	True	43.6	**M**	**M**	100%
4.	50.0	50.0	True	52.1	**M**	**M**	100%
5.	28.3	38.0	True	22.9	**L**	**L**	100%
6.	40.4	44.0	True	46.2	**M**	**M**	100%
7.	46.4	48.8	True	52.1	**M**	**M**	100%
8.	52.4	65.7	True	51.9	**M**	**M**	100%
9.	62.9	71.7	True	54.5	**M**	**M**	100%
10.	66.9	80.1	True	37.9	**L**	**L**	100%
11.	68.1	52.4	True	71.2	**H**	**H**	100%
12.	68.1	22.3	True	69.7	**H**	**H**	100%

Table 3.7. Model results evaluation for the initial environmental parameters, namely, temperature (ΔT), and humidity (ΔH) for 12 sampled control experiments [2].

Expt. No.	ΔCO(ppm)	ΔCO_2(ppm)	ΔO_2 (ppm)	Flame Presence	EFIP (%)	Test Model	Actual Model	Determined Accuracy Rate (%)
1.	23.6	21.4	23.6	True	47.8	**M**	**M**	100%
2.	32.4	29.1	28.0	True	63.2	**H**	**H**	100%
3.	36.8	30.2	31.1	True	69.1	**H**	**H**	100%
4.	44.5	32.4	39.0	True	71.3	**H**	**H**	100%
5.	50.0	37.9	44.5	True	75.0	**H**	**H**	100%
6.	19.2	48.9	51.1	True	56.5	**M**	**M**	100%
7.	13.7	8.2	13.7	True	25.0	**L**	**L**	100%
8.	64.3	50.0	17.0	True	86.5	**VH**	**VH**	100%
9.	70.9	24.7	32.4	True	62.8	**H**	**H**	100%
10.	32.4	46.7	65.4	True	70.3	**H**	**H**	100%
11.	48.9	75.3	86.3	True	25.0	**L**	**L**	100%
12.	57.7	69.8	62.1	True	60.9	**H**	**H**	100%

Table 3.8. Model results evaluation for gas combustion, namely, carbon monoxide (ΔCO), carbon dioxide (ΔCO_2) and oxygen (ΔO_2) for 12 sampled control experiments[2].

From Table 3.7, Expt. 1, it is observed that when (ΔT) is 9.0 °C, (ΔH) is 17.5%, and the EFIP is 17.6%. Hence, the test case is L and the actual case is VL. This gives an accuracy rate of 50%. Whereas, Expt. 2, ΔT is 15.1 °C, ΔH is 27.3% and the EFIP is 18.3%, as the probability of a fire occurrence. Thus, test case is L and, actual case is VL, gives an accuracy rate of 50%. In Expt. 3, we illustrate that when, ΔT is 38.0 °C, ΔH is 58.4% and the EFIP is 43.6%. Hence, 43.6% there is a probability of a fire occurrence. The test case is M and the actual case is M giving an accuracy rate of 100%.

From Expt. 4 – 12, it is observed that, the accuracy rate is 100%, meaning the tested model is working according to the defined fuzzy inference rules. Then, the above method is subsequently applied to dataset of the dissipated gases in Table 3.8. Then, the overall accuracy rate of the model determined using;

$$\text{Test Model Accuracy Rate (\%)} = \sum \frac{\mu(\mathbf{ai})}{\mathbf{n}} \qquad (3.5)$$

From Eqn. (3.5), the accuracy rate of the model is determined, μ(ai) denotes the percentage accuracy of each experiment, and n denotes the total number of simulated experiments, giving, an overall average accuracy of 95.83 %. Thus, using fuzzy logic significantly improves the accuracy of the model design for effective early fire detection.

The novel idea of using Mamdani's FIS method exhibits a significant improvement in rate accuracy for the proposed model. Hence, translating into an effective early fire detection system design for appropriate safety and control within urban markets of EA. This study, achieved an accuracy rate of 95.83% compared to related works (ref. Sect. 3.6.3). Unlike the human patrol mechanisms, the proposed solution is cheaper and highly affordable compared to satellite systems, for the development of effective fire detection systems for safety control within urban markets in East Africa (E.A). The solution, realized that application of multi-sensory fire detection systems minimizes false alarms, compared to single sensor smoke detection systems. Hence, the application of the fuzzy logic technique, improved the overall accuracy of the model to 95.83% as defined in the inference rules.

Expt. No.	EFIP-ΔT	FL Value-(ΔT)	EFIP-ΔG	FL Value-(ΔG)	Fire Status	FL Output Value Mapping [0-1]
1.	17.6	0.25	47.8	0.5	**VH**	**1**
2.	18.3	0.25	63.2	0.75	**H**	**0.75**
3.	43.6	0.5	71.3	0.75	**M**	**0.5**
4.	52.1	0.5	75	0.75	**L**	**0.25**
5.	22.9	0.25	56.5	0.5	**VL**	**0**
6.	46.2	0.5	25	0.25		
7.	52.1	0.5	86.5	1		
8.	51.9	0.5	62.8	0.75		
9.	54.5	0.5	70.3	0.75		
10.	37.9	0.25	25	0.25		
11.	71.2	0.75	60.9	0.75		
12.	69.7	0.75	69.1	0.75		

Table 3.9: Shows the Overall Performance Evaluation of EFIP Mapped to Corresponding FL-Value of (ΔT, ΔG) in the Range of [0-1].

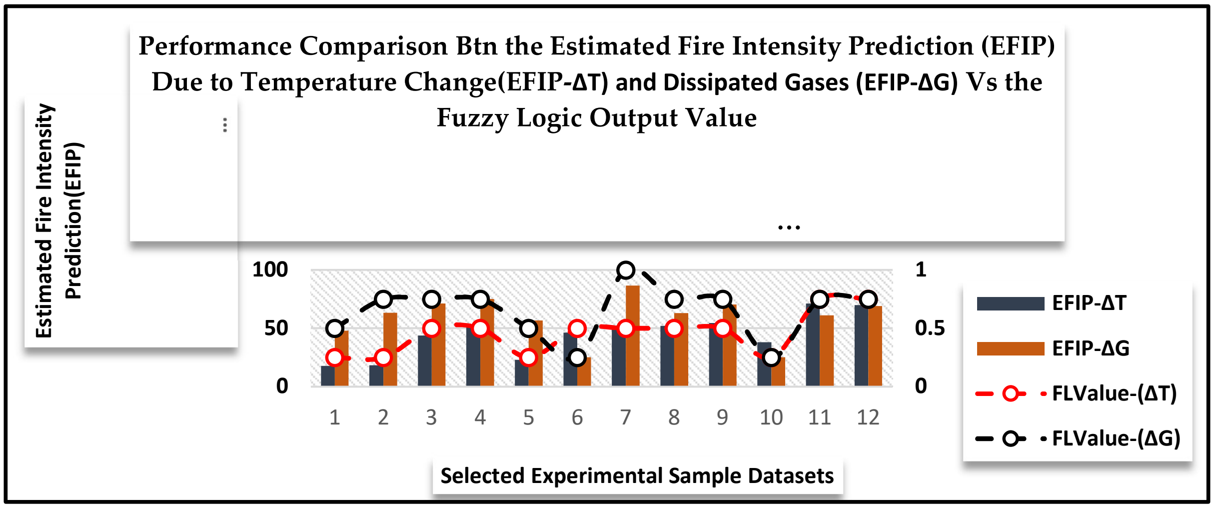


Fig. 3.13: The Overall Performance Evaluation of EFIP due to ΔT, ΔG Respectively Mapped to their Corresponding FL-Value.

In Fig. 3.13, we examine an overall performance evaluation of the result experiment that is determined by mappings of parameters, i.e., EFIP-ΔT and EFIP-ΔG respectively. The mappings were linked to their corresponding fuzzy logic output Value of say, FL Value (ΔT), FL Value (ΔG) (ref. Table 3.9).

Obtained results indicate that, at Expt. No., 1-5, a higher performance of EFIP-ΔG yielded compared to EFIP-ΔT, is due to higher CO_2 and CO concentrations dissipated. Hence, a higher overall EFIP-ΔT. At Expt. 10, it is observed that the performance of EFIP-ΔT is in equilibrium with EFIP-ΔG where FL-Value = 0.25 to 0.75. This is because, at Expt. 10-12; fire combustion is at its peak value; hence, the maximum heat transfer is equivalent to the amount of gases that are completely dissipated into the atmosphere. Hence, the fire status can be determined through their corresponding mappings, ranging from Very Low (VL) to Very High, with FL-values of 0 and 1, respectively.

3.6.3 Comparison Between the Proposed Fuzzy Detection Model and Related Works.

In Sect. 3.6.3, a comparative performance study is conducted among related works to compare the accuracy rate of the various techniques used in fire detection against the proposed solution and the results a summarized as follows.

Features.	Kaur et al., (2019)[34]	Sawar et al., (2018)[24]	Abedi et al., (2019)[43]	Sowah *et al.,* (2020)[44]	Proposed Fuzzy Detection Model
Input Parameters Used	Temperature, Humidity, Smoke and Flame	temperature, humidity, Time and Flame.	Smoke, Temperature and Humidity.	Smoke, Temperature Humidity and Flame.	Temperature, Humidity, CO, CO_2, O_2 and Flame.
Methods or Techniques	K-means Clustering, adaptive ANFIS	Single Simulated Expt. Model, Using Fuzzy Logic, Method.	Analytical Network Processing (ANP), Fuzzy Logic.	Fuzzy Logic Method, Trained CNN a deep learning technique.	Two separate Integrated Simulated Expt. Models, Using Fuzzy Logic, Method.
Accuracy Rate (%)	93.12%	95.8%	81.9%	94.0%	95.83%
False alarm detection	Sends Early warning signals	Yes; Notification Warnings	Generates a forest fire risk map.	Yes; Web notification Platform.	Yes; Determination of Fire Intensity Status Notifications Followed with Appropriate Action.
Decision on two authentications method.	No	Yes.	No.	No.	Yes.

3.6.4 The Proposed IoT Fuzzy Based Detection Model.

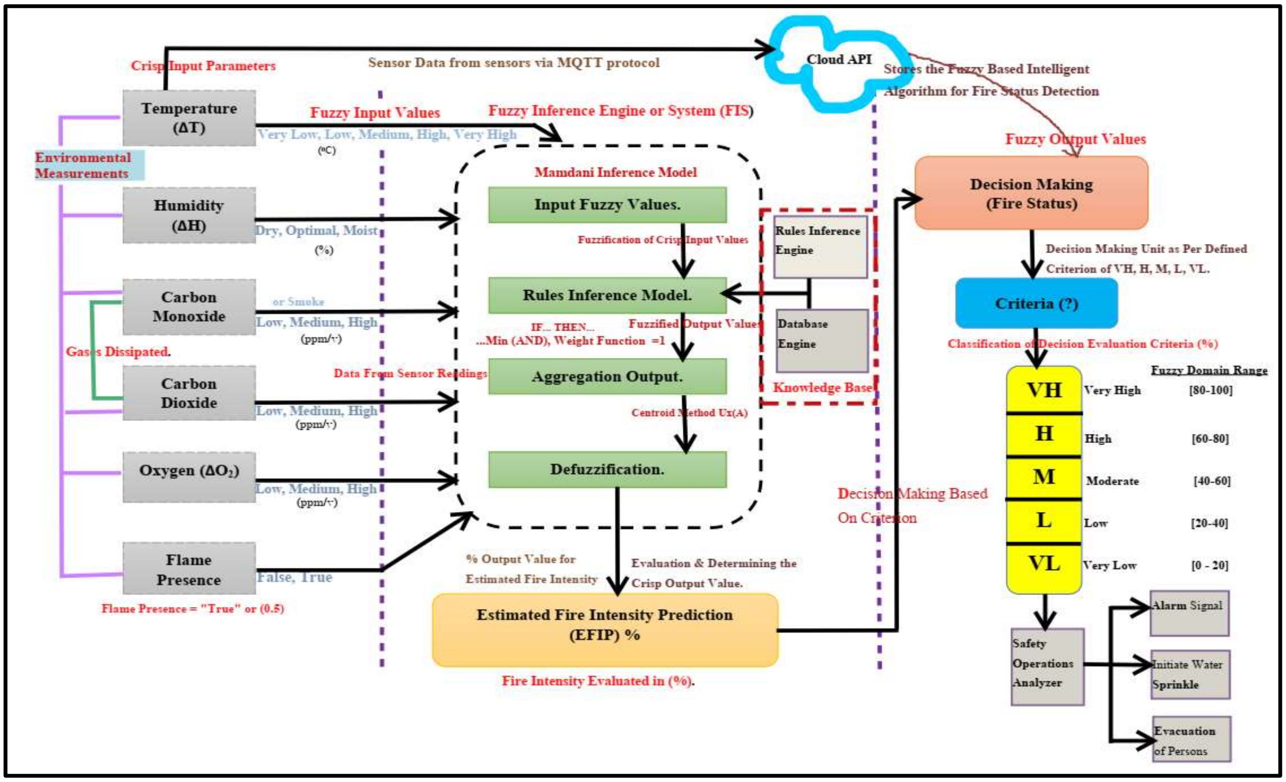


Fig. 3.14: Proposed IoT-based Fuzzy Detection Model[2].

The model consists of five components, i.e., i) fuzzy input values, ii) fuzzy inference engine (FIS), iii) fuzzy output values, iv) decision evaluation criteria, and v) safety operations analyzer.

i. Fuzzy Input Values:

Is comprised of crisp input parameters, containing sensors of different data readings. Each input parameter represents a fuzzy input. Sensor data is read, i.e. (ΔT) = {very low, low, medium, high, very high}, (ΔH) = {dry, optimal, moist}, carbon monoxide (ΔCO) = {low, medium, high}, (ΔCO_2) = {low, medium, high}, (ΔO_2) = {low, medium, high}, and flame presence = {false, true}. Then, data readings from sensors are fuzzified into the different input fuzzy values (cf. Fig. 3.14).

ii. The Fuzzy Inference Engine (FIS):

Through fuzzification, fuzzy values are processed using microcontroller unit (MCU). It contains the inference rules engine applied to the model. The database engine includes a fuzzy associative matrix (FAM) to store all inference rules employed by the model, which is eventually combined to generate a knowledge base. Using the provided fuzzy domain, the minimum probability of a fire outbreak is determined using the "AND" operator and the IF...THEN structure. Within the fuzzy inference system (FIS), all inference rules are defined by a weighted function value (W = 1).

iii. The Fuzzy Output Values:

The fuzzy output defines the output criteria value, which represents the model's implication. The data is subsequently sent to the cloud API using the Message Queue Telemetry Transport (MQTT) protocol. To calculate the EFIP, the input is processed using an intelligent fuzzy algorithm. EFIP denotes the probability of a fire occurring based on the input fuzzy parameters. As a result, an informed choice is taken to identify the current fire situation “fire status”.

iv. The Decision Evaluation Criteria:

The EFIP outputs an informed decision reflecting the percentage (%) of a fire status using predefined classification criterion ranges, namely, very low (VL): [0–20], low (L): [20–40], moderate (M): [40–60], high (H): [60–80], and very high (VH): [80–100].

The proposed algorithm, intelligently processes data to make an informed decision. It should be noted that data is stored in the Thing Speak cloud API.

v. Safety and Operations Analyzer:

This component is engaged because an early warning fire was identified. A signal in the form of a message is sent to the authorities in order for them to respond immediately. The safety and operations analyzer sends an alert notification, activates a water sprinkler, or sends a warning message in preparation for an immediate evacuation.

3.7 Conclusion & Future Works.

The study proposes an IoT-based fuzzy detection model based on the Mamdani FIS to aid in effective fire safety management and control for the surrounding market community. The mode's significance is focused at early fire detection by reducing substantial damage via signaling authorities. According to related works, a variety of techniques are used in fire detection. However, the study utilized a multisensory approach for effective fire detection using fuzzy logic to minimize false alerts. Six input parameters were used in the modeling, namely, temperature change (ΔT), humidity (ΔH), carbon dioxide (ΔCO_2), carbon monoxide (ΔCO), oxygen (ΔO_2) and flame presence, with a varying fuzzy range vis-à-vis the EFIP. If any anomalies are detected within the environment, then the system notifies the responsible authorities. EFIP, is the percent probability of a true fire being detected, and then action is instigated through an alarm signal or a water sprinkler to suppress any prevailing fires detected using a fuzzy detection algorithm. Simulation results using the MATLAB Fuzzy Logic toolbox, realized an accuracy of 95.83%. Future work intends to design a lightweight interval type-2 fuzzy algorithm to increase the accuracy of fire detection in the local markets of East Africa.

CHAPTER 4

INTERVAL TYPE-2 TSK MODEL FOR INTELLIGENT FIRE INTENSITY DETECTION ALGORITHM WITH DECISION MAKING IN LOW-POWER DEVICES

Chapter 4 was developed based on the following article: E. Lule, C. Mikeka, A. Ngenzi and D. Mukanyiligira, "Interval type-2 fuzzy model for intelligent fire intensity detection algorithm with decision making in low-power devices," Intelligent Automation & Soft Computing, vol. 38, no.1, pp. 57–81, 2023.

4.1 Introduction

Within the densely populated areas of urban marketplaces in East Africa, fire disasters are among the most commonly encountered phenomena. For example, the recurrent fire outbreaks that threaten Gisozi, Rwanda; Gikomba, Kenya; and Owino, Uganda, regularly cause serious property damage and the loss of lives totaling millions of shillings. However, the small-scale vendor communities rely on these markets as a source of income to sell their regular goods. According to the annual police reports, electrical short circuits, negligence, and carelessly neglected charcoal stoves are among the main causes of these fires [3][5], [17].

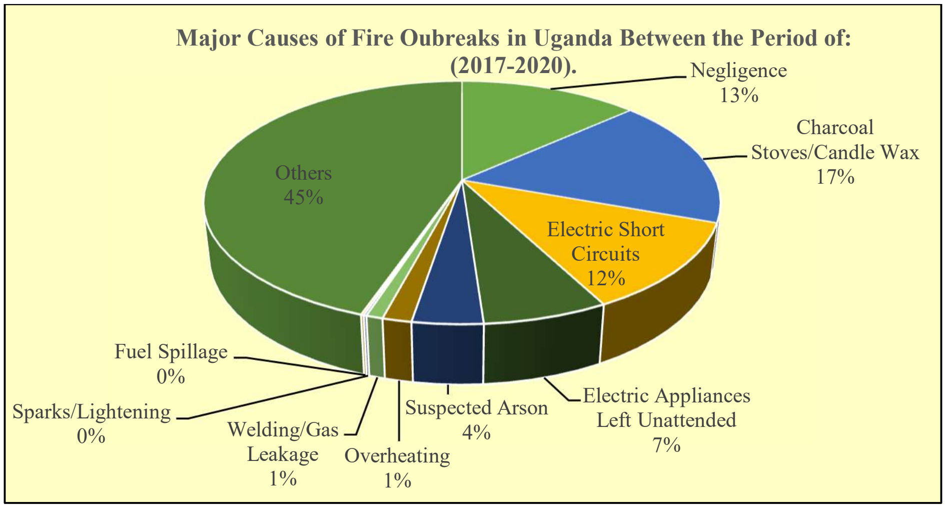


Fig. 4.1: The Primary Causes of Fire Outbreaks in Uganda Between the Period of (2017-2020)
Source: Uganda Police Annual Reports; Dept. of Fire & Rescue Services Between (2017-2020)[6][1].

Vendor communities heavily rely on the human patrol observation methods for any sightings of a fire outbreaks, and thereafter inform the fire brigade call centers for action. However, this method is highly ineffective and may result in significant property damage to the vendor due to unnecessary delays [1][2]. Single smoke detectors exhibit high rate of false alarms due to their high sensitivity to the surrounding environment [45][46]. Ruchkin *et al.* [47][8][11]proposed a satellite-based system; however, it's quite expensive to acquire and maintain for the least developed countries (LDCs). Camera systems, also pose an inability to monitor the initial start-up surface fires[48][49]. The study used a free, open-source fuzzy toolbox integrated with MATLAB 2018a software to investigate the performance of the Interval Type-2 (IT2) Tang Sugeno Kang (TSK) fuzzy model. The IT2 TSK model achieved a performance of 98.2% compared to Mamdani's Type-1 (T1) fuzzy model of 95.8%, as reported by E. Lule *et al*[2]. Because of the additional degrees of freedom provided by the footprint of uncertainty (FOU) present in their IT2 fuzzy sets. The study further proposes an intelligent fire intensity detection algorithm based on the IT2 TSK fuzzy model to determine an informed decision for low-power devices. Type-2 systems are better able to overcome the dimensionality issue that leads to the high computational complexity associated with fuzzy rule-based systems [50][51]because they employ more consequential parameter design.

To increase the effectiveness of the model, the IT2 TSK fuzzy model minimizes the inherent errors in Type-1 fuzzy systems [52][38]]. Thus, the suggested detection algorithm can be implemented in hardware prototypes of low-cost, low-power, and easily reproducible fire detection solutions to aid public safety protection for any fire incidents by providing early warning systems to the local market community.

4.2 Materials and Methods

The study used a free, open-source Interval Type-2 fuzzy toolbox integrated with MATLAB 2018a. The tool is widely used by designers of Type-2 fuzzy control systems. In order to study the performance of the IT2 TSK model, the tool was carefully configured and integrated with MATLAB 2018a [53][54]. MATLAB [55][56] is a multi-paradigm computing tool that enables modeling and simulation of real-time engineering solutions. Two input parameters were used: fire intensity due to temperature change ($\widetilde{\mathbf{FI}_{\mathbf{T}}}$), and fire intensity due to dissipated gases ($\widetilde{\mathbf{FI}_{\mathbf{G}}}$) i.e., CO_2 and CO. The output fire intensity ($\widetilde{\mathbf{FI}_{\mathbf{T}}}$), of the IT2 TSK fuzzy model is considered to minimize errors created by T1 fuzzy systems. We assumed that flame presence was "true" for all fuzzy inference rule outcomes. The best-fit dataset for the IT2 TSK fuzzy is determined using regression analysis. To compute the accuracy of the model, error parameters like mean absolute error (MAE), mean square error (MSE), and root mean square error (RMSE) are used to determine the best choice of dataset. The number of fuzzy inference rules (N =17) is sampled. The dataset with the lowest RMSE value is identified as the best-fitting data for the model.

4.3 Second-Order Fuzzy Associative Matrix (2 FAM)

FAM is a content addressable memory for storing the fuzzy inference rules for a particular associated fuzzy model [57]. This study utilized the 2FAM method, with Interval Type-2 (IT2) fuzzy input sets defined as the crisp input values for the proposed TSK fuzzy model. Using second-order derivatives, the output fuzzy values of Mamdani's Type-1 (T1) fuzzy sets, become Type-2 inputs. Type-2 fuzzy logic systems (FLS) are gaining popularity due to the inherent errors created by T1 fuzzy systems, can be minimized by Type-2 fuzzy systems [58][59]. This improves the accuracy of the model to design perfectly working fuzzy control systems in real time. Dr. Loft (1975) denoted as Type-1 systems by A and associated Type-2 systems by Ã [60][61]. So, the associated order n is explicitly defined for n =1,2,3…N. Table 4.1 shows the generated 2FAM rules for the IT2 TSK fuzzy model. **Note:** The model considers six significant sparse rules to minimize the high computational costs associated with Type-2 fuzzy systems.

Interval Type-2 TSK Sparse Fuzzy Inference Rule (FIR) Design.

The table 4.1, shows the interval type-2 input parameters (($\widetilde{\mathrm{FI}}_{\mathrm{T}}$), ($\widetilde{\mathrm{FI}}_{\mathrm{G}}$) and the optimized outcome value ($\widetilde{\mathrm{FI}}_{\mathrm{O}}$) ranging from [0-100] or [0-1] fuzzy range. The derived IT2 sparse inference rules are then represented in Table 4.4. In the Tables 4.2, we represent the Interval Type-2 input parameters and their membership function. And Table 4.3, represents the overall output value for the proposed optimized model.

The Optimized Fire Intensity ($\widetilde{FI}_O$)		Fire Intensity Due to Gases Dissipated ($\widetilde{FI}_G$)				
Fire Intensity Due to Temperature Changes ($\widetilde{FI}_T$)	($\widetilde{FI}_T$, $\widetilde{FI}_G$)	VLow	Low	Moderate	High	VHigh
	Low	**VL**	**L**	-	-	-
	Moderate	-	-	**M**	-	**H**
	High	-	-	-	**H**	**VH**

Table 4.1: The Proposed IT2 TSK Sparse Fuzzy Inference Rules (FIR) with Output Value ($\widetilde{\mathbf{FI}}_{\mathbf{O}}$)

Crisp Input Variables.	**IT2 TSK Fuzzy Input Parameters.**	**Fuzzy Domain Range.**	**Universe of Discourse for MFs**
Fire Intensity due Temp. Change ($\widetilde{FI}_T$)	Low, Moderate, High.	[0-100] % or [0-1]	0-40, 40-80, 80-100 or 0-0.4, 0.4-0.8, 0.8-1 respectively.
Fire Intensity due Gas Dissipated ($\widetilde{FI}_G$**).**	Very Low, Low, Moderate, High, Very High.	[0-100] % or [0-1]	0-20, 20-40,40-60, 60-80 and 80-100 or 0-0.2, 0.2-0.4, 0.4-0.6, 0.6-0.8, 0.8-1 } respectively.

Table 4.2: Defined IT2 TSK Input Parameters Used for the Proposed IT2 TSK Fuzzy Model

Crisp Output Variable	**IT2 TSK Fuzzy Output Parameter**	**Fuzzy Domain Range (%)**	**Universe of Discourse MF**
Proposed Optimized Fire Intensity Output Value ($\widetilde{\mathbf{FI}}_{\boldsymbol{o}}$)	Very Low, Low, Medium, High, Very High	[1-100] or [0-1]	{0-20, 20-40, 40-60, 60-80, 80-100} or {0-0.2, 0.2-0.4, 0.4-0.6, 0.6-0.8, 0.8-1}

Table 4.3: Crisp Output Parameter Considered for the Proposed Interval Type-2 TSK Fuzzy Model.

4.4.1 Interval Type-2 TSK Decision Parameters for Inputs and Outputs of the Proposed Fuzzy Model

The proposed IT2 TSK fuzzy model makes use of secondary input $\widetilde{\mathbf{FI}}_{\mathbf{T}}, \widetilde{\mathbf{FI}}_{\mathbf{G}}$ and output $\widetilde{\mathbf{FI}}_{\boldsymbol{o}}$ parameters to fully understand the fuzzy model's performance behavior. The universe of discourse for the various crisp input and output parameters is defined in Tables 4.2 and 4.3 as below;

S/No.	T1 Input Variables		IT2 TSK Output Variables	
#Rule No	**($\widetilde{\mathbf{FI}}_{\mathbf{T}}$)**	**($\widetilde{\mathbf{FI}}_{\mathbf{G}}$)**	**($\widetilde{\mathbf{FI}}_{\mathbf{O}}$)**	**“Fire Status” Decision**
1.	Low	VLow	VL	Very Low
2.	Low	Low	L	Low
3.	Moderate	Moderate	M	Moderate
4.	High	High	H	High
5.	Moderate	VHigh	H	High
6.	High	VHigh	VH	Very High

Table 4.4: Derived IT2 TSK Sparse Fuzzy Inference Rule Sets for the Model, With Inputs ($\widetilde{\mathbf{FI}}_{\mathbf{T}}$, $\widetilde{\mathbf{FI}}_{\mathbf{G}}$) Vs the Optimized Fire Intensity Output Value ($\widetilde{\mathbf{FI}}_{\mathbf{O}}$).

***NB:** Proposed Optimized Fire Intensity Output denoted by $\widetilde{\mathbf{FI}}_{\mathbf{O}}$ = {VL, L, M, H, VH}

4.4.2 Algorithm Design Procedure

In Fig. 4.2, a basic algorithm schematic of two Mamdani's Type-1 fuzzy model is reported by E. Lule et al.,[2]. **$EFIP_1$** and **$EFIP_2$** are the Mamdani's T1 outputs. For effective fire detection, the proposed algorithm considers; temperature, humidity, CO_2, CO, and flame. The oxidation process uses oxygen by reacting with the carbon element present in any burning material to produce two dissipated gases, CO_2 and CO. The fuzzy algorithms' schematics assume thresholds ***Th*** and ***Thg*** to determine the minimal temperature rise and gas dissipation. Likewise, **FI** is the optimal fire intensity detection value $\widetilde{\mathbf{FI}}_{\boldsymbol{o}}$ obtained by the proposed detection algorithm.

4.4.3 Algorithm Assumptions Considered.

The study considered four key assumptions of the proposed algorithm to ensure that the optimal fire intensity $\widetilde{\mathbf{FI}}_{\boldsymbol{o}}$ detection value realized;

i. Proposed lab. Expt. assumes three key parameters for fire combustion i.e., temperature (ΔT), and two by product dissipated gases; carbon dioxide (ΔCO_2), and carbon monoxide (ΔCO).

ii. To reduce the computational complexity associated with Type-2 fuzzy systems, the study employs six Interval Type-2 TSK sparse inference rules to optimize the performance of the fire intensity detection algorithm.

iii. Humidity (ΔH) is not considered as a parameter for combustion because it's dependent on the temperature (ΔT) and pressure of the environment.

iv. For each inference rule defined, flame presence is a Boolean probability that can be evaluated as "true" or "false". So, because of the high computational overheads associated with Type-2 fuzzy systems, output processing with centroid TR and defuzzification methods may be a bottleneck on IT2 fuzzy systems. Hence, alternative approaches, such as the Nie-Tan method [29][30], can be suggested.

In the Fig 4.3, we show an abstract of Algorithm 1 and Algorithm 2 snapshot for fire detection using Mamdani's fuzzy applications methods. Algorithm 1 represented the estimated fire intensity prediction due to temperature changes ($EFIP_1$), and Algorithm 2, is derived from the estimated fire intensity prediction due to gas dissipated ($EFIP_2$). Further detailed discussion of the proposed algorithms (1 &2) in Fig. 4.2 are represented by E. Lule *et al* in [2].

Algorithm 1: The Estimated Fire Intensity Prediction (**EFIP$_1$**) Due to Temperature Change

```
Initialize: Crisp Input: $\Delta T$, $\Delta H$;
Define: Crisp Output: EFIP$_1$;
Initialize: Set_Flame ←“True’;
Define: Th //As the Threshold Value for Temperature;
Apply the Type-1 Fuzzy Logic Construct:
while ($\Delta T > Th$)
{//Apply Fuzzy Inference Rules
    if ($\Delta T$ is Low AND $\Delta H$ is Dry)
        then EFIP$_1$ ← “LOW”
    Else if ($\Delta T$ is Medium AND $\Delta H$ is Optimal)
        then EFIP$_1$← “MODERATE”
    Else if ($\Delta T$ is Very Low AND $\Delta H$ is Optimal)
        then EFIP$_1$← “LOW”
    Else if ($\Delta T$ is High AND $\Delta H$ is Dry)
        then EFIP$_1$← “HIGH”
    Else if ($\Delta T$ is Medium AND $\Delta H$ is Dry)
        then EFIP$_1$← “MODERATE”
    Else if ($\Delta T$ is Very High AND $\Delta H$ is Moist)
        then EFIP$_1$← “LOW”
    Else if ($\Delta T$ is Very High AND $\Delta H$ is Optimal)
        then EFIP$_1$← “HIGH”
    Else if ($\Delta T$ is Very High AND $\Delta H$ is Dry)
        then EFIP$_1$ ← “HIGH”

                    .... Rule n
    End if
}
End while Loop
```

Algorithm 2: The Estimated Fire Intensity Prediction **(EFIP$_2$)** Due to Gas Dissipated**.**

```
Initialize: Crisp Input: $\Delta CO_2$, $\Delta CO$, $\Delta O_2$;
Define: Crisp Output: EFIP$_2$;
Initialize: Set_Flame ← “True’;
Define: Thg; //As the Threshold Value for Gas Dissipated;
Apply Type-1 Fuzzy Logic Construct:
while ($\Delta CO_2 > Thg$)
{//Apply the Fuzzy Inference Rules
    if ($\Delta CO_2$ is Low AND $\Delta CO$ is Low AND $\Delta O_2$ is Low)
        then EFIP$_2$← “L”
    Else if ($\Delta CO_2$ is Low AND $\Delta CO$ is Medium AND $\Delta O_2$ is Medium)
        then EFIP$_2$←“M”
    Else if ($\Delta CO_2$ is Medium AND $\Delta CO$ is Medium AND $\Delta O_2$ is Medium)
        then EFIP$_2$← “H”
    Else if ($\Delta CO_2$ is High AND $\Delta CO$ is Dry AND $\Delta O_2$ is Low)
        then EFIP$_2$← “HIGH”
    Else if ($\Delta CO_2$ is Low AND $\Delta CO$ is Dry AND $\Delta O_2$ is Low)
        then EFIP$_2$← “VH”
    Else if ($\Delta CO_2$ is Low AND $\Delta CO$ is Dry AND $\Delta O_2$ is Low)
        then EFIP$_2$← “VH”
    Else if ($\Delta CO_2$ is Very High AND $\Delta CO$ is Optimal AND $\Delta O_2$ is Low)
        then EFIP$_2$← “HIGH”
    Else if ($\Delta CO_2$ is Very High AND $\Delta CO$ is Dry AND $\Delta O_2$ is Low)
        then EFIP$_2$← “HIGH”
                    .... Rule n
    End if
}
End while Loop
```

Fig. 4.2: Derived Type 1 Mamdani’s Fuzzy Based Algorithms for Output Fire Intensity Due Temperature Change (EFIP$_1$) and Dissipated Gas (EFIP$_2$) Output Respectively, Due Combustion[2].

4.5 Framework of the Proposed Fire Intensity Detection Algorithm

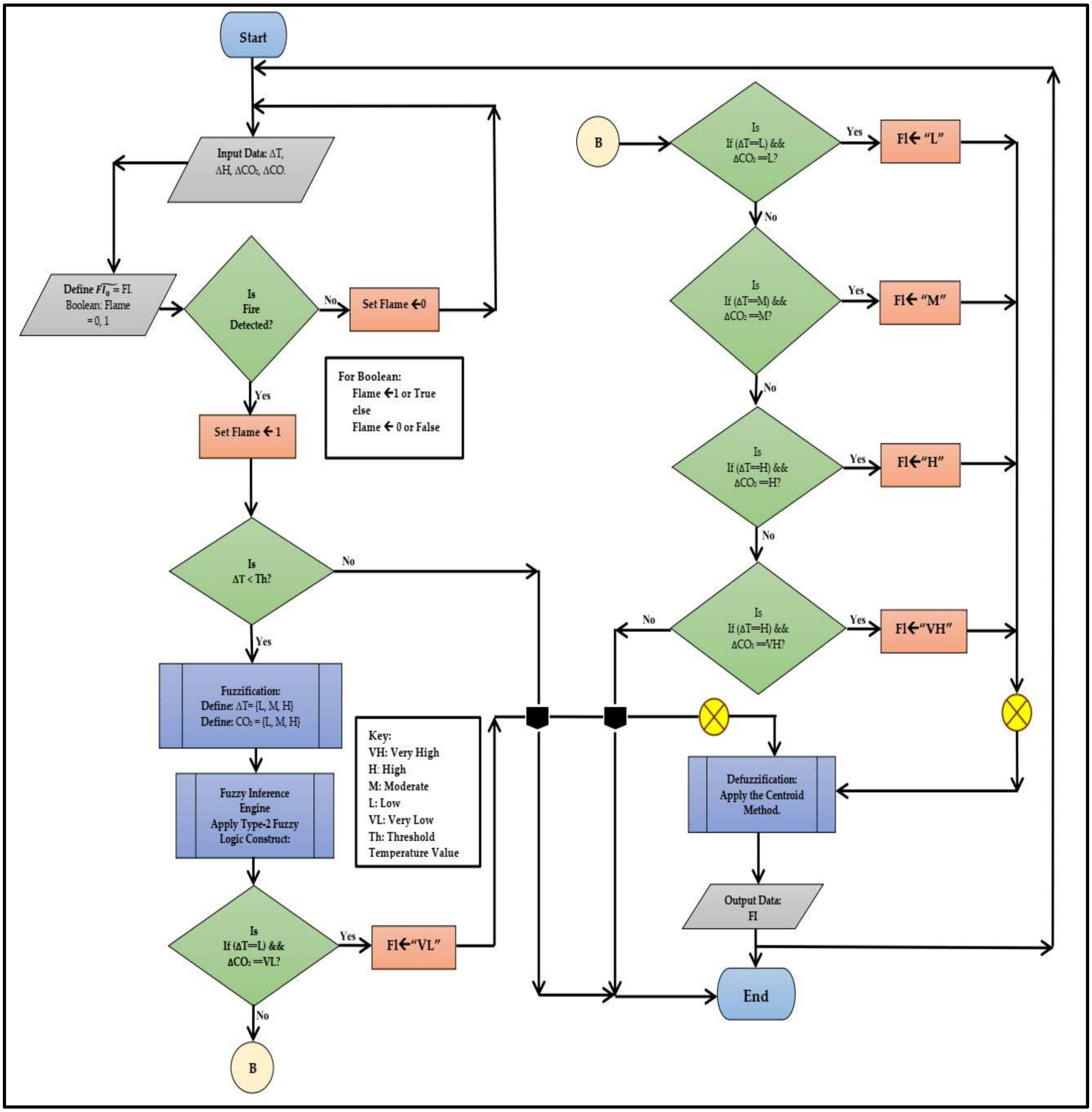


Fig. 4.3: Framework Workflow Diagram of the Proposed Interval Type-2 TSK Fire Intensity Detection Algorithm

Key: **FI** = Fire Intensity Output Fuzzy Set = {Low (**L**), Medium (**M**), High (**H**), Very High (**VH**)}

4.5.1Proposed Fire Intensity Detection Algorithm Procedure Based on Interval Type-2 (IT2) TSK Fuzzy Approach

For efficient fire detection, the suggested algorithm 3 takes into account the parameters, rate of change in CO_2, temperature, CO and flame presence = 1 or "True". Given that rising temperatures have an effect on humidity, the presence of fire may not be greatly changed. Lines 13 through 22 illustrate the fuzzy inference rule, with Low, Medium, and High being the three possible outcomes. The result outcome of the rules is called fire intensity (FI).

Algorithm 3: The Proposed Intelligent Fire Intensity Detection Algorithm Based on Interval Type-2 TSK Fuzzy Model.

```
1.  Begin:
2.  Initialize: $\Delta T$, $\Delta H$, $\Delta CO_2$, $\Delta CO$;
3.  Define: $\widetilde{FI_0}$ =FI;
4.  Set Boolean:  setFlame0←0, setFlame1←1;
5.  if fire is detected?
6.      True: set_Flame1 ←1; go to: 11
7.      else
8.      False: set_Flame0 ← 0; go to: 3
9.  do {
10.      Define: $\Delta T$ ← {L, M, H},
11.      Define: $\Delta CO_2$ ← {L, M, H};
12.      {  // Applying the Fuzzy Concept for Fire Intensity Detection
13.      if ($\Delta T$==" L" AND $\Delta CO_2$=="VL" or CO=="VL")
14.      then FI ← "VL"
15.      Else if ($\Delta T$==" L" AND $\Delta CO_2$==" L" or CO==" L")
16.      then FI ← " L" next
17.      Else if ($\Delta T$=="M" AND $\Delta CO_2$=="M" or CO=="M")
18.      then FI ← "M" next
19.      Else if ($\Delta H$=="M" AND $\Delta CO_2$=="H" or CO=="H")
20.      then FI ← "H"
21.      Else if ($\Delta T$=="H" AND $\Delta CO_2$==" VH" or CO==" VH")
22.      then FI ← "VH"
23.    End if
24.    }
25.      Output Value:  FI;
26.      }
27.      while ($\Delta T$<Th && ($\Delta CO_2$ < Thg); go to: 3
End Loop:
```

4.5.2 Fire Intensity Detection Model Using Interval Type 2 TSK Fuzzy Approach.

The fire intensity detection model is comprised of temperature, humidity, CO_2, and CO data acquisition unit, IT2 TSK model training unit, and a fire status decision making unit. In Fig. 4.5, the proposed Interval Type-2 TSK fuzzy based algorithm trains on the obtained dataset to make an informed decision of a prevailing fire status.

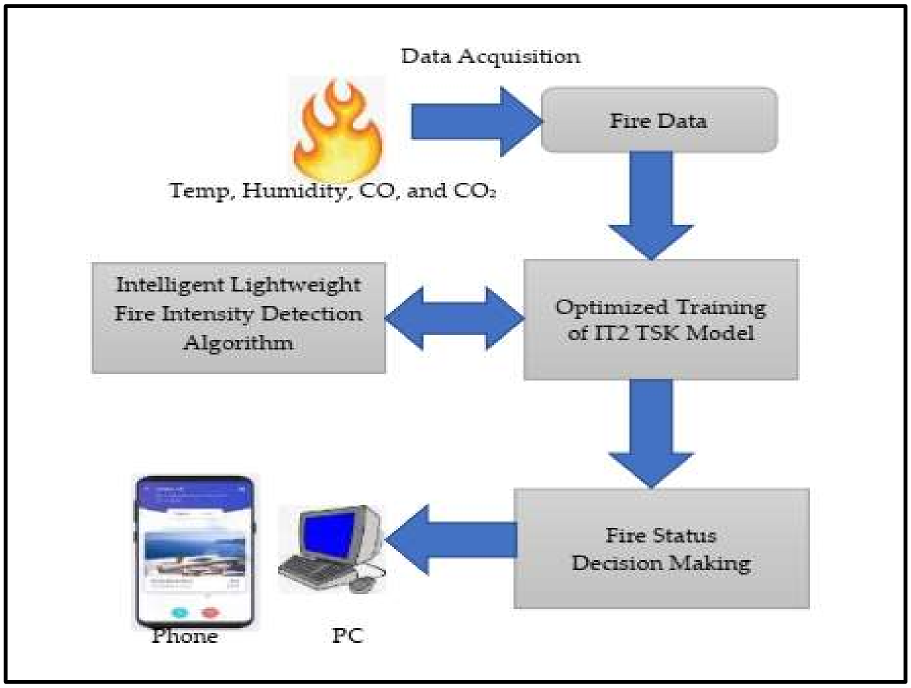


Fig. 4.5: The Proposed Breakdown of the Interval Type-2 TSK Fuzzy Detection Model

4.5.3 Schematic Hybrid Structure of an Interval Type-2 TSK Fuzzy Control Model.

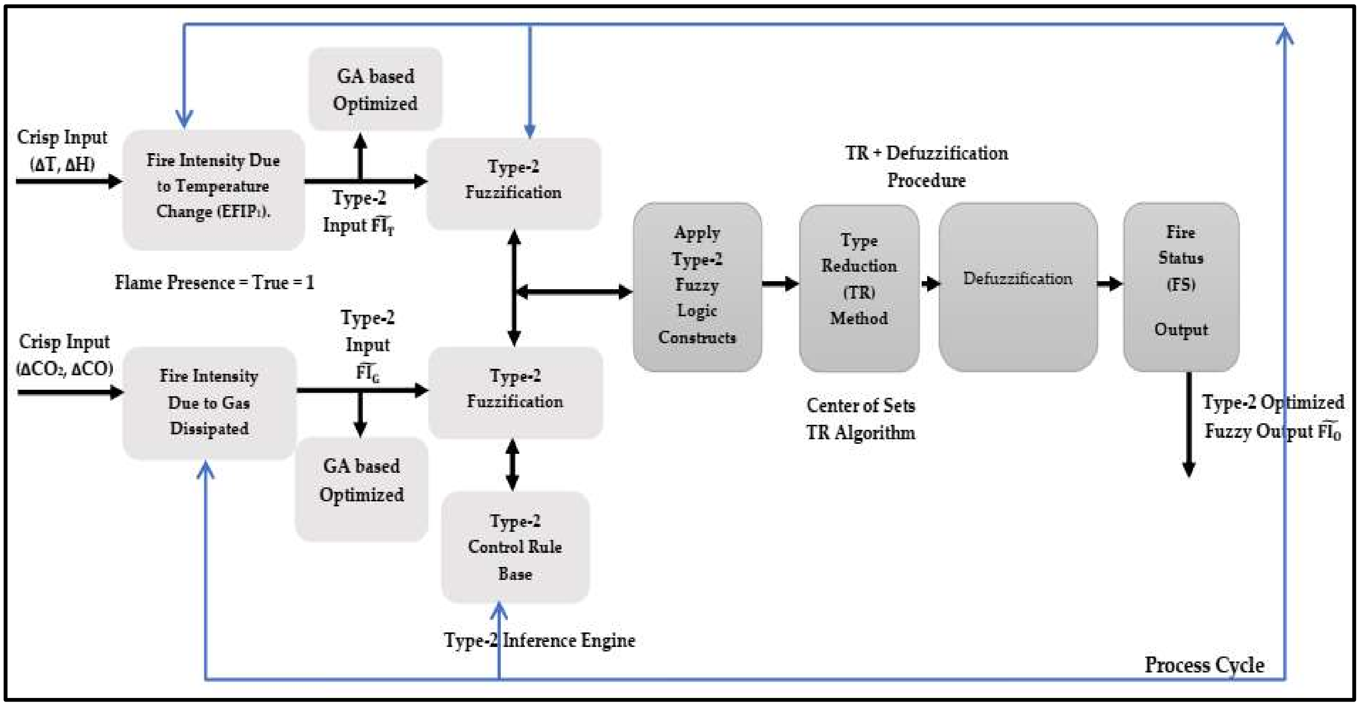


Fig. 4.6: Hybrid Structure of an Interval Type-2 TSK Fuzzy Model

The Interval Type-2 fuzzy systems handles better uncertainties due to the nature of their membership functions, and better tailored for situations where external noise exits. The study provides an IT2 TSK lightweight fire intensity detection method for efficient decision-making in low power devices to test resilience of Type-2 (T2) systems[62]. Type-2 (T2) fuzzy systems deliver a smoother control route compared to T1 systems, hence increased average accuracy[63][64]. Fig. 4.6, provides a hybrid of IT2 fuzzy system design. Parameters, ΔT, ΔH, ΔCO_2, and ΔCO, defined as primary T1 fuzzy control inputs for IT2 model. T1 inputs yielded T1 outputs based on a genetic algorithm (GA). Such that: EFIP1, and EFIP2, define the Fire Intensity due Temperature Change, and gas dissipated respectively due to combustion. Fire intensity is the amount of heat transferred per unit time, represented as (%). IT2 fuzzy systems embrace an additional stage called, Type Reduction (TR) Method. The Takagi Sugeno Kang (TSK) were naturally upgraded by introducing IT2 fuzzy logic formalism to support the higher levels uncertainty boundaries that are inherent in T1 FLC systems [65][66]. $\widetilde{FI_T}$, and $\widetilde{FI_G}$ are secondary discrete inputs of IT2 fuzzy system. TR is a defuzzification method used to transform Type-2 sets into equivalent T1[67]. TR method is an extended version of Type-1 defuzzification method for computing the centroid of Type-2 output fuzzy sets to minimize uncertainty errors [68][58]. For better performance, the algorithm considers six sparse inference rules, because too many rules increase the computational burden of fuzzy system. Thus, an optimized output of fire status denoted a ($\widetilde{\mathbf{FI_O}}$) is determined.

4.6 Relational Mathematical Theory and Notations in Type-2 Fuzzy Systems

Type-2 fuzzy sets define a non-deterministic truth degree with imprecision and uncertainty for each set component [69][70]. Fuzzy inference systems utilize fuzzy reasoning and set theory principles to map fuzzy inputs to fuzzy outputs. This method is used in a variety of applications, i.e., computer vision, pattern recognition, and intrusion detection[47][39]. T1 systems represent membership as the membership of each element in a fuzzy set, whereas IT2 fuzzy sets represent membership as crisp intervals bound by the display range [-1 1][71]. T1 fuzzy systems have been utilized in a variety of fields, although they are typically associated with noisy data and extremely large uncertainties and error limits, as represented in the inference rule consequents[72][73]. Thus, from fuzzy set theory, the application of IT2 TSK fuzzy inference systems can be correlated using mathematical theoretical representations. Let U be the initial Universe of Objects, EU, the set of parameters about the objects modelled, P(U) the power set of U such that: $\boldsymbol{A} \subseteq \boldsymbol{E}$. Molodtsov [70][74] defines a set as; A pair (F, A) called the soft set over U, where F is a mapping given by: F: A → P(U). For ε Є A, F(ε) is defined as a set of ε- approximate elements of the soft set (F, A). For Type-2 fuzzy sets denoted by Ã is also characterized by general type-2 membership function for, $\mu\tilde{A}$ ($\boldsymbol{x}$, U) such that: U defines a finite and non-empty set which is referred to as a universe of discourse[75].

Hence; $U x I \rightarrow I$ where; $\mathbf{x} \in U$, $I = [0,1]$ and $\mu \in J_x \subseteq I$

$\tilde{A} = \{(x, u), \mu_{\tilde{A}}(x, u) | x \in u, u \in J_x \subseteq I\}$ for: $0 \leq \mu_{\tilde{A}}(x, u) \leq 1$

$$\tilde{A} = \int_{x \in \mu} \int_{\mu \in J_x} \frac{\mu\tilde{A}(x,u)}{(x, u)} = \int_{x \in \mu} \frac{\int_{\mu \in J_x} f_x(u)/u}{x} \quad J_x \subseteq 1 \tag{4.1}$$

where $f_x(u) = \mu_{\tilde{A}}(x, u)$

Hence, for the class of type-2 fuzzy sets of the Universe U is denoted by $F_{T2}(U)$.

4.7 Operations of General Type-2 Fuzzy Sets

If U is to be a nonempty universe such that $\widetilde{\mathbf{A}}, \widetilde{\mathbf{B}} \in F_{T2}(U)$: then,

$$\widetilde{\mathbf{A}} = \int_{x \in u} \frac{\mu_{\tilde{A}}(x)}{x} \int_{x \in u} \frac{\left[\int_{x \in J_x^u} f_x(u)/u\right]}{x}, \quad J_x^u \subseteq I \quad \widetilde{\mathbf{B}} = \int_{x \in u} \frac{\mu_{\tilde{B}}(x)}{x} \int_{x \in u} \frac{\left[\int_{\gamma \in J_x^\gamma} g_x(\gamma)/\gamma\right]}{x}, \quad J_x^\gamma \subseteq I \tag{4.2}$$

Hence, by applying the general type-2 fuzzy operations to the aforementioned fuzzy sets, defined from Eqns. in (4.1 - 4.2), i.e., union, intersection, and complement, give rise to equations (4.3), (4.4), and (4.5) respectively, for the model design and can be explicitly simplified and reduced as follows to realize a faster computational execution time;

$$\mu_{\widetilde{A}\,u\,\widetilde{B}}(x)=\int_{u\in j_x^u}\int_{\gamma\in j_x^\gamma}\frac{[f_x(u)\wedge g_x(u)]}{u\vee\gamma}=U_{\widetilde{A}}(x)\sqcup U_{\widetilde{B}}(x),\ x\in U \tag{4.3}$$

$$\mu_{\widetilde{A}\,n\,\widetilde{B}}(x)=\int_{u\in j_x^u}\int_{\gamma\in j_x^\gamma}\frac{[f_x(u)\wedge g_x(u)]}{u\wedge x}=U_{\widetilde{A}}(x)U_{\widetilde{B}}(x),\ x\in U \tag{4.4}$$

$$\mu_{\sim\widetilde{A}}(x)=\neg\mu_{\widetilde{A}}(x)=\int_{u\in j_x^u}\frac{f_{x\,(u)}}{1-\mu} \tag{4.5}$$

Where, $\wedge$ denotes the t-norm minimum operator, $\vee$ the maximum operator and $\sqcup$ is the joint operation, $\mu_{\widetilde{A}\,u\,\widetilde{B}}(x)$, $\mu_{\widetilde{A}}(x)$, $\mu_{\widetilde{B}}(x)$are the secondary membership functions and all belonging to Mamdani's type-1 fuzzy sets.

4.8 IT2 TSK Fuzzy Inference Systems vis-à-vis Decision Making.

An IT2 fuzzy set (FS) can be characterized by the Eqn. (4.6) below;

$$\widetilde{\mathbf{A}} = \int_{x\in X}\{\int_{\mu\in J_x} 1/\mu\}/\mathbf{x},\ J_x\subseteq[0\ 1] \tag{4.6}$$

Where, the secondary grades of $\widetilde{\mathbf{A}}$ are equal to 1 and X is the primary domain with input $\boldsymbol{x}$ and primary degree membership $\boldsymbol{\mu}$. J_x, is the secondary domain with values varying from [0 -1]. The IT2 fuzzy set can therefore be best described by having the Lower (LMF) or $\underline{u}_{\widetilde{A}}(x)$ and Upper Membership Functions (UMF) or $\overline{u}_{\widetilde{A}}(x)$. Therefore, the given shaded region in Fig. 4.7, between LMF and UMF is called the "*Footprint of Uncertainty (FOU)*". Thus, the FOU represents a third-dimensional value of member function (MF) at each point on its two-dimensional domain such that;

$$\text{FOU}(\widetilde{\mathbf{A}}) = U_{x\in X}\left[\underline{u}_{\widetilde{A}}(x), \overline{u}_{\widetilde{A}}(x)\right] \tag{4.7}$$

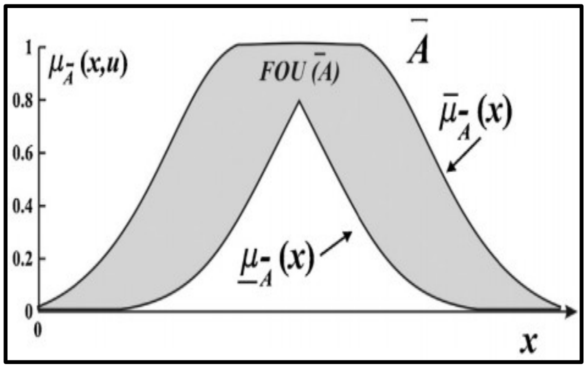


Fig. 4.7: Shows the Interval Type-2 Fuzzy Set with shaded region Known as the FOU[75].

From Eqn. (4.6), using the IT2 TSK fuzzy systems approach of rules firing strength, we can determine the minimal probability for a given fire status. Thus, we can determine the fire status using the **IF...THEN** structure for the fuzzy inference consequent decision evaluation[67][76]. Upon this background, if we consider a typical T1 TSK sparse rules-based approach[77] comprised of n inference rules then;

R1: **IF** $\mathbf{x_1}$ *is* $\mathbf{A_1^1}$ and **…** $\mathbf{x_k}$ *is* $\mathbf{A_k^1}$ and **…** $\mathbf{x_q}$ *is* $\mathbf{A_q^1}$ **THEN** $y = \boldsymbol{f}_1\boldsymbol{x}_1^1(\ldots \mathbf{x}_q^1,)$,

…

Rn: **IF** $\mathbf{x_1}$ *is* $\mathbf{A_1^n}$ and **...** $\mathbf{x_k}$ *is* $\mathbf{A_k^n}$ and **…** $\mathbf{x_q}$ *is* $\mathbf{A_q^n}$ **THEN** $y = \mathbf{f_n}(\mathbf{x_1^n}\ldots,\mathbf{x_q^n})$,

where A_j^i (i $\in\{1,2\ldots n\}$ and j$\in\{1,2\ldots q\}$)

Alternatively, if we assume that the IT2 TSK sparse rules approach comprised of n rules then a zero or first-order polynomial function can be derived as follows;

R₁: **IF** $\mathbf{x_1}$ *is* $\mathbf{\widetilde{A}_1^1}$ and **…** $\mathbf{x_k}$ *is* $\mathbf{\widetilde{A}_k^1}$ and **…THEN** *y* $=\mathbf{\tilde{p}_0^1+\tilde{p}_1^1x_1^1+\ldots\tilde{p}_k^1x_k^1}$

Rᵢ: **IF** $\boldsymbol{x_1}$ *is* $\mathbf{\widetilde{A}_1^i}$ and **…** $\mathbf{x_k}$ *is* $\mathbf{\widetilde{A}_k^i}$ and **…THEN** *y* $=\mathbf{\tilde{p}_0^i\tilde{p}_1^ix_1^1+\ldots\tilde{p}_k^ix_k^i}$

…

Rₙ: **IF** $\mathbf{x_1}$ *is* $\mathbf{\widetilde{A}_1^n}$ and **…** $\mathbf{x_k}$ *is* $\mathbf{\widetilde{A}_k^n}$ and **…THEN** *y* $=\mathbf{\tilde{p}_0^n+\tilde{p}_1^ix_1^n+\ldots\tilde{p}_k^nx_k^n}$

where $\widetilde{A}_j^i$ (j∈{1, …k} and i∈{1, …n}) is defined as an IT2 fuzzy set having an input variable $\boldsymbol{x_j}$in the $\boldsymbol{i^{th}}$rule, giving a consequence in the crisp polynomial function as:

$y = f_i(x_j, \ldots\ldots x_k)=\tilde{p}_0^n+\tilde{p}_1^ix_1^n+\ldots\tilde{p}_k^nx_k^n$ where $\tilde{p}_j^i$ are crisp intervals or consequent parameters for a given universe of discourse such that; $\mathbf{O}\ (\mathbf{\widetilde{A}_1^*}\ \ldots.\mathbf{\widetilde{A}_k^*})$, $\mathbf{\widetilde{A}_j^i}$, antecedent value of rule R_i. Using the related IT2 TSK fuzzy model approach of Jie Li *et al.*[78] the approximate firing strength ($\overline{\boldsymbol{\alpha}}_{\boldsymbol{i}}$), of matching degree s and antecedent variable x_j, using a t-norm operator* can be deduced to the Eqn. (4.8);

$$\underline{f}= \underline{u}_{\widetilde{A}_1}(x_1) * \underline{u}_{\widetilde{A}_2}(x_2)* \ldots *_{\widetilde{A}_n}(x_n);$$

$\bar{f}= \bar{u}_{\widetilde{A}_1}(x_1) * \bar{u}_{\widetilde{A}_2}(x_2)*\ldots. *\bar{u}_{\widetilde{A}_n}(x_n)$, then the firing strength ($\overline{\boldsymbol{\alpha}}_{\boldsymbol{i}}$) can be deduced as follows:

$$(\bar{\alpha}_i) = s\left(\overline{\widetilde{A}_1^i}, \overline{\widetilde{A}_1}\right) \wedge \ldots.\wedge\ s\left(\overline{\widetilde{A}_k^i}, \overline{\widetilde{A}_k}\right) \tag{4.8}$$

Applying, the type reduction (TR) and defuzzification methods, using the center of sets we can compute the centroid of every consequent set. Then the weighted average of each consequent determined as follows;

$$Y = [y_1, y_r] = \int_{\boldsymbol{y^1}} \ldots \int_{\boldsymbol{y^m}} \int_{f^1} \ldots \int_{f^m} 1 \Big/ \frac{\sum_{i=1}^m f^i y^i}{\sum_{i=1}^m f^i} \tag{4.9}$$

Y is the interval set, determined by the constants $y_i$and y_r f^i is $[\underline{f}^i, \bar{f}^i]$.

$\boldsymbol{y^i}= [\boldsymbol{y_i^i},\ \boldsymbol{y_r^i}]$ is the centroid of type-2 interval fuzzy set in the consequent part. Karnik and Mendel[58]shows two endpoints are dependent on the mixture of $\underline{f}^i$and $\bar{f}^i$ values, can be determined as;

$$\boldsymbol{y_r} = y_r\left(\underline{f}^1, \ldots, \underline{f}^R,\ \ \bar{f}^{R+1} \ldots\ldots \bar{f}^m, y_r^1,\ \ y_r^m\right)$$

$$y_i = y_i\left(\bar{f}^1, \ldots.\bar{f}^m,\ \ \underline{f}^{l+1} \ldots\ldots \underline{f}^m, y_i^1,\ \ y_i^m\right) \tag{4.10}$$

Note that (y_r, y_i) are determined by using Eqn. (4.10). A special iterative formula was then was developed by Karnik and Mendel[68] to produce the computation values of $y_{r(max)}$ and $y_{i\ (min)}$ as;

$$y_r = \frac{\sum_{i=1}^R \underline{f}_i\ y_i^r + \sum_{i=R+1}^m \bar{f}_i y_i^r}{\sum_{i=1}^R \underline{f}_i + \sum_{i=R+1}^m \bar{f}_i}$$

$$y_i = \frac{\sum_{i=1}^L \bar{f}_i\ y_i^l + \sum_{i=L+1}^m \bar{f}_i y_i^l}{\sum_{i=1}^L \bar{f}_i + \sum_{i=L+1}^m \underline{f}_i} \tag{4.11}$$

Thus, the switch points can be determined by using Karnik-Mendel's (KM) algorithm[68][58]. Therefore, the crisp outputs in the defuzzification layer can then be computed as follows;

$$y = \frac{y_r + y_l}{2} \tag{4.12}$$

4.9 Type Reduction.

Type Reduction (TR) is a phase used to defuzzify type-2 fuzzy sets (FSs) that transform Type-2 into Type-1 FSs. T1 and IT2 fuzzy systems differ such that IT2 FSs employ an extra TR procedure to process IT2 FSs. The KM type reduction method, is widely used to calculate the type reduced sets in an iterative manner [56]. Other methods include; Iterative Algorithm with Stop Condition (IASC), Enhanced IASC, Enhanced Opposite Direction Searching Algorithm (EODS), Wu-Mendel Uncertainty Bound Method (WM), Nie-Tan (NT) and Begian-Melek-Mendel(BMM)[55]. The study, used the enhanced KM algorithm because, it improves the computational costs and significantly captures most features, such as adaptiveness and stability, of the IT2 model. The major bottleneck of type-2 fuzzy systems is output processing using centroid TR and the defuzzification method. Since KM algorithms are associated with high computational costs, this may hinder them from real time application[65]. Thus, to compromise between speed, computational overload, and complexity, other methods were proposed, i.e., Nie-Tan method, to compute the output of the IT2 TSK fuzzy system[79][80]. N refers to the number of system inputs, such that: n = 1,2,3…. N.

Algorithm 4: Computing the Output with TR, Using Centroid, Type Reduced Sets.

```
   Compute $y_l$
1. Initialize
   $a = \sum_{n=1}^{N} \underline{y}^n \underline{f}^n$
   $b = \sum_{n=1}^{N} \underline{f}^n$
   L =0
2. Compute $y_l$
   L=L+1
   $a = a + \underline{y}^L (\bar{f}^L - \underline{f}^L)$
   $b = b + \bar{f}^L - \underline{f}^L$
   $y_l = a/b$
3. if ($y_l \leq y^{L+1}$), stop
   otherwise, go to: step 2
```

```
   Compute $y_r$
1. Initialize
   $a = \sum_{n=1}^{N} \bar{y}^n \underline{f}^n$
   $b = \sum_{n=1}^{N} \underline{f}^n$
   R=N
2. Compute $y_r$
   $a = a + \bar{y}^R (\bar{f}^R - \underline{f}^R)$
   $b = b + \bar{f}^R - \underline{f}^R$
   $y_r = a/b$
   R =R-1
3. if $y_r \geq y^R$, stop;
   otherwise, go to: step 2
```

Then, the Nie-Tan method can therefore be mathematically defined using the Eqn. (4.13) below;

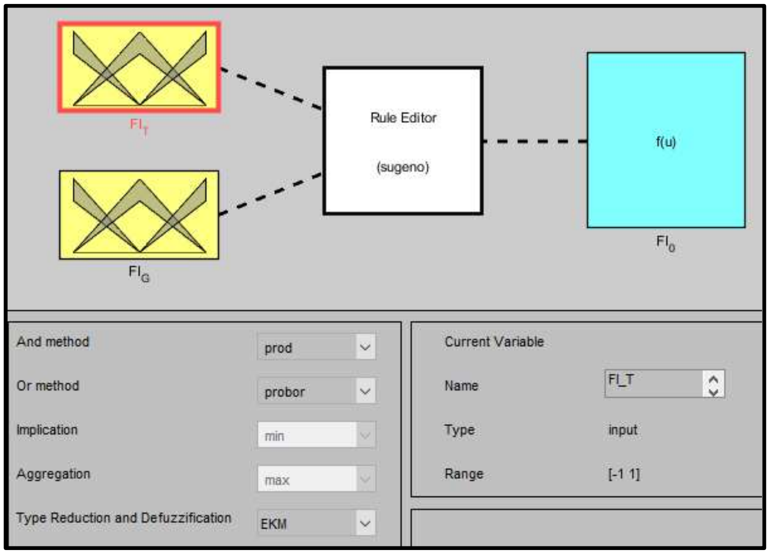
$$y = \frac{\sum_{n=1}^{N} y^n (\underline{f}^n + \bar{f}^n)}{\sum_{n}^{N} (\underline{f}^n + \bar{f}^n)} \tag{4.13}$$

4.9.1 Simulation Lab. Experiment Setup.

Fig. 4.8, shows an Interval Type-2 (IT2) Takagi Sugeno Kang (TSK) FLS design model editor using MATLAB 2018a. We use a free open source IT2 MATLAB fuzzy logic toolbox integrated within the MATLAB2018a. Because, its widely used in modeling and simulation of type-2 fuzzy systems[56]. The model uses TSK inference system to ensure higher performance efficiency realized for the proposed fire detection algorithm. IT2 TSK fuzzy logic systems (FLS) design has additional defuzzification step called *Type Reduction*. We consider t-norm operators i.e., minimum or product as a scale factor for training the IT2 TSK model design for decision making using sparse inference r ules[81]. Through "***Fuzzification***", crisp input parameters: $\widetilde{\mathbf{FI}}_{\mathbf{T}}$ = {Low, Moderate, High}; and, $\widetilde{\mathbf{FI}}_{\mathbf{G}}$ =

{Very Low, Low, Moderate, High, Very High.} are defined (Table 4.2). NB: All sparse rules considered have same weighted priority function of (W=1) using the "***and***" operator.

In the design of IT2 TSK model, an enhanced Karnik-Mendel (eKM) type reduction method is used to ensure lower computational complexity and certainly lower uncertainty error bounds encountered compared to Karnik-Mendel (KM)[58]. The model uses trimf M, having offset members with the "***Defuzzification***" values of the interval output (Table 4.3). For $\widetilde{\mathbf{FI}}_{\mathbf{O}}$ = {VLow, Low, Moderate, High and VHigh} represented in range of [0-100]. Using six "sparse inference rules" approach, the overall optimal performance outcome can be viewed in Fig. 4.9(a-d).



And method: prod
Or method: probor
Implication: min
Aggregation: max
Type Reduction and Defuzzification: EKM

Current Variable
Name: FI_T
Type: input
Range: [-1 1]

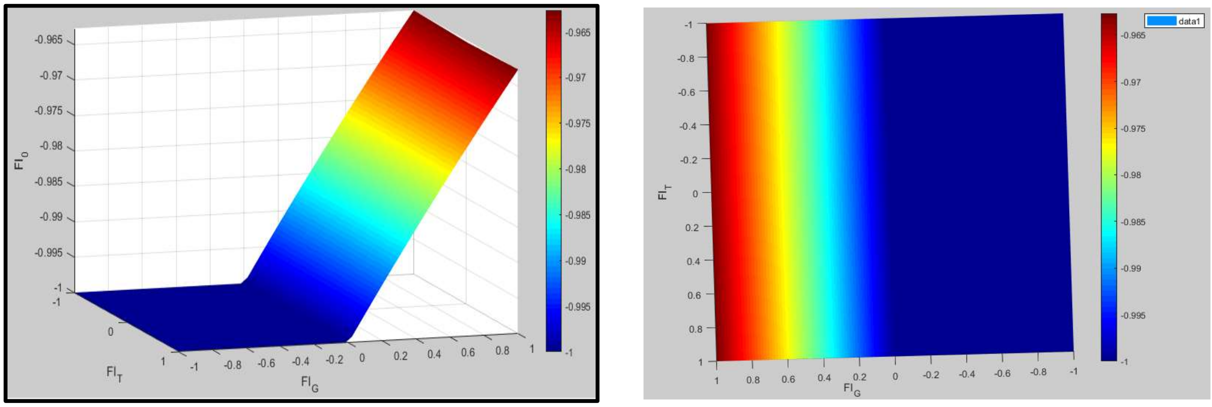
Fig. 4.8: Main Model Editor for the IT2- TSK FLS with Inputs: ($\widetilde{\mathbf{FI}}_{\mathbf{T}}$), ($\widetilde{\mathbf{FI}}_{\mathbf{G}}$) IT2 and Crisp Output: ($\widetilde{\mathbf{FI}}_{\mathbf{O}}$) Overall Optimized Fire Intensity.

4.9.2 Results and Discussion

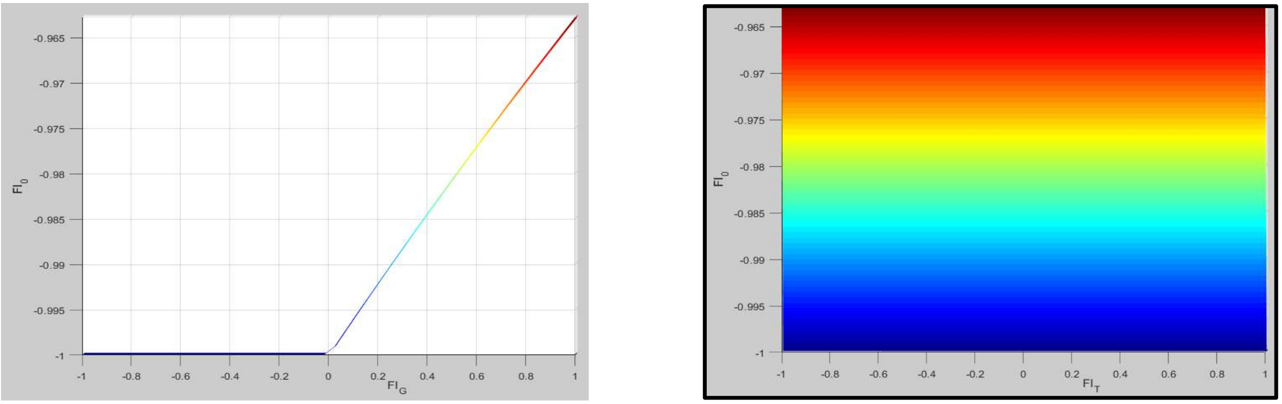
Results were obtained by integrating a free open-source fuzzy toolbox of IT2 with the MATLAB 2018a environment [27]. The tool was used to investigate the IT2 TSK model's performance. Two input parameters are taken into account: Fire intensity due to gases dissipated $\widetilde{\mathrm{FI}}_{\mathrm{G}}$ and Fire intensity due to temperature change $\widetilde{\mathrm{FI}}_{\mathrm{T}}$. The optimized fire intensity ($\widetilde{\mathrm{FI}}_{\mathrm{O}}$) is determined from the correlation between $\widetilde{\mathrm{FI}}_{\mathrm{G}}$ Vs $\widetilde{\mathrm{FI}}_{\mathrm{T}}$. Based on six (6) significant IT2 TSK sparse rules approach (Table 4.4), the eKM type reduction algorithm was used to reduce the computational complexity associated with Type-2 fuzzy systems. Fig. 4.9(a-d) shows a 3D, 2D surface control view of the IT2 TSK model of a continuous discrete color pattern separations using MATLAB 2018a.

Software:	**Hardware:**
Simulation Software: MATLAB 2018a	**Specifications:**
Interval Type-2 MATLAB Fuzzy Toolbox Ver. 1.2	**Type:** Hp Laptop ak0xx
Configurations Settings:	**Processor Type:** AMD A9 Radeon Graphics R5 Processor
Crisp Input Parameters: $\widetilde{\mathbf{FI}}_{\mathbf{T}}$= {Low, Moderate, High}, $\widetilde{\mathbf{FI}}_{\mathbf{G}}$ = {Very Low, Low, Moderate, High, Very High}; **Output Crisp Parameter** $\widetilde{\mathbf{FI}}_{\mathbf{O}}$ = {VLow, Low, Moderate, High, VHigh}, **Type-1 Fuzzy Inference Range:** [0-100]	**Memory:** 12 GB RAM
Member Function (MF) = **trimf**, range: **[**0.6 – 0.**2**]	**Hard Drive Capacity:** 1 TB HDD
Crisp Output Type = "Interval".	**Operating System**: Windows 10 Prof.
Crisp Interval Type-2 Fuzzy Output Range: [**-1 1**]	**Wireless Network Adapter:** 802.11g/n
Implication Connector Operator: "and"	
Offset Configurations: **UMF**= [20.73 0.65 -10.73 1.55 1], **LMF** = [0.7582 0.9 1 0.6]	
Number of Sparse Fuzzy Inference Rules: (N = 6).	
Type Reduction Algorithm: enhanced Karnik-Mendel (eKM)	
Weighted Priority Function: (W=1)	

Table 4.6: Experimental Steup Configuration Parameter Settings



(a) $\widetilde{\mathbf{FI}}_{\mathbf{G}}$, $\widetilde{\mathbf{FI}}_{\mathbf{T}}$Vs $\widetilde{\mathbf{FI}}_{\mathbf{O}}$ (b) $\widetilde{\mathbf{FI}}_{\mathbf{G}}$ Vs $\widetilde{\mathbf{FI}}_{\mathbf{T}}$



(c) $\widetilde{\mathbf{FI}}_{\mathbf{G}}$ **Vs** $\widetilde{\mathbf{FI}}_{\mathbf{O}}$ **(d)** $\widetilde{\mathbf{FI}}_{\mathbf{T}}$**Vs** $\widetilde{\mathbf{FI}}_{\mathbf{O}}$

Fig. 4.9(a-d): Shows a 2D, 3D surfaces control view results outputs of the IT2 TSK fuzzy model of a continuous discrete colour pattern separations using MATLAB 2018a.

Several insights can be drawn;

i. The Interval Type-2 TSK model's effective fire intensity surface control results range from [-1, 1]. The obtained linear discrete model pattern (Fig. 4.8a) demonstrates that any change in $\widetilde{FI}_G$ or $\widetilde{FI}_T$ gradually influences the output of $\widetilde{FI}_O$. For example, an increase in both $\widetilde{FI}_G$ and $\widetilde{FI}_T$ significantly increases $\widetilde{FI}_O$. Hence, FI_O increases the fire intensity risk with higher changes in $\widetilde{FI}_G$ or $\widetilde{FI}_T$, and vice versa, through the combustion process.

ii. Fig. 4.8(b-d) shows a moderately higher $\widetilde{FI}_T$ with increasing temperature change, resulting in a higher risk of gases dissipated FI_G due to performance. Hence, increased output performance of FI_O visa viz increased FI_T and $\widetilde{FI}_G$.

iii. Fig. 4.9c depicts an increase in fire intensity due to gasses dissipated FI_G, which increases the $\widetilde{FI}_O$. As a result of the gas combustion, the fire output risk increases. Similarly, as shown in Fig. 4.9d, an increase in temperature changes FI_T and increases FI_O. As a result, using general type-2 fuzzy systems gradually improves the performance of the IT2 TSK model's final output design.

iv. Fig. 4.8(b-d), increased ΔT yield FI_O. As a result, increased fire intensity risks associated with temperature change may occur. Fig. 4.8c shows a significant increase in gases dissipated, i.e. (CO_2, CO), yielding increased FI_O and, as a result, greater fire intensity from blue to yellow region (Fig. 4.8c).

Fire Intensity Due Temperature ($\widetilde{FI}_T$)	Fire Intensity Due to Gas Dissipated ($\widetilde{FI}_G$)	Optimized Fire Intensity Output ($\widetilde{FI}_O$)
0.4286	0.102	0.9958
0.2653	0.1429	1
0.7143	1	1
0.7143	0.1429	0.9943
0.8367	0.2653	0.9895
0.7551	0.3469	0.9864
0.7959	0.4694	0.9818
0.1837	0.5102	0.9804
0.02041	0.5918	0.9774
0.3061	0.4286	0.9834
0.2653	0.551	0.9788
0.4286	0.6327	0.9758
0.3878	0.7959	0.97
0.3061	1	0.9629
0.8367	0.9184	0.9656
0.8776	0.7551	0.9713
0.6327	0.5102	0.9803

Table 4.7: Dataset Shows the Relationship Between($\widetilde{FI}_T$, $\widetilde{FI}_G$) and Optimized Fire Intensity Output ($\widetilde{FI}_O$) Using the absolute values in normalized range [0-1].

SNo.	EFIP$_1$(%)	EFIP$_2$(%)	$(\widetilde{\mathbf{FI}}_{\mathbf{O}})$(%)
1	17.6	47.8	99.5
2	18.3	63.2	100
3	43.6	69.1	100
4	52.1	71.3	99.4
5	22.9	75	98.9
6	46.2	56.5	98.6
7	51..9	25	98.1
8	52.1	86.5	98
9	54.5	62.8	97.7
10	37.9	70.3	98.3
11	71.2	25	97.8
12	69.7	60.9	97.6

Table 4.8: Sampled Extracted Dataset Results for Mamdani's Type-1 Fuzzy Outputs (**EFIP$_1$, EFIP$_2$**) Vs Interval Type-2 TSK Output Value $(\widetilde{\mathbf{FI}}_{\mathbf{O}})$.

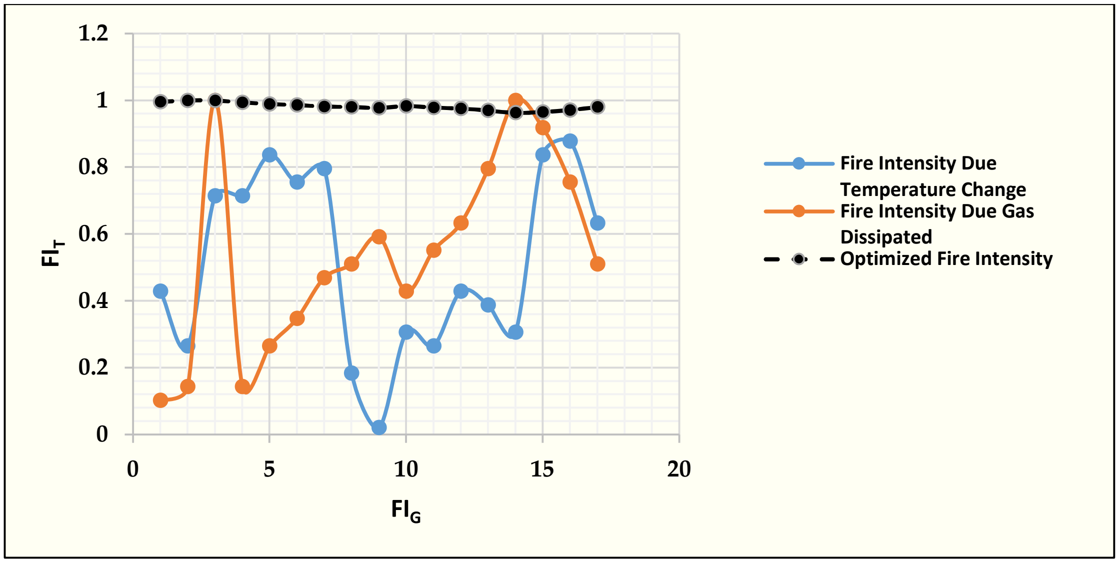


Fig. 4.10: Performance of the IT2 TSK Fuzzy Model Vs Absolute Values of $\widetilde{FI}_T$, $\widetilde{FI}_G$ Vs $\widetilde{FI}_O$ in [0-1] normalized range.

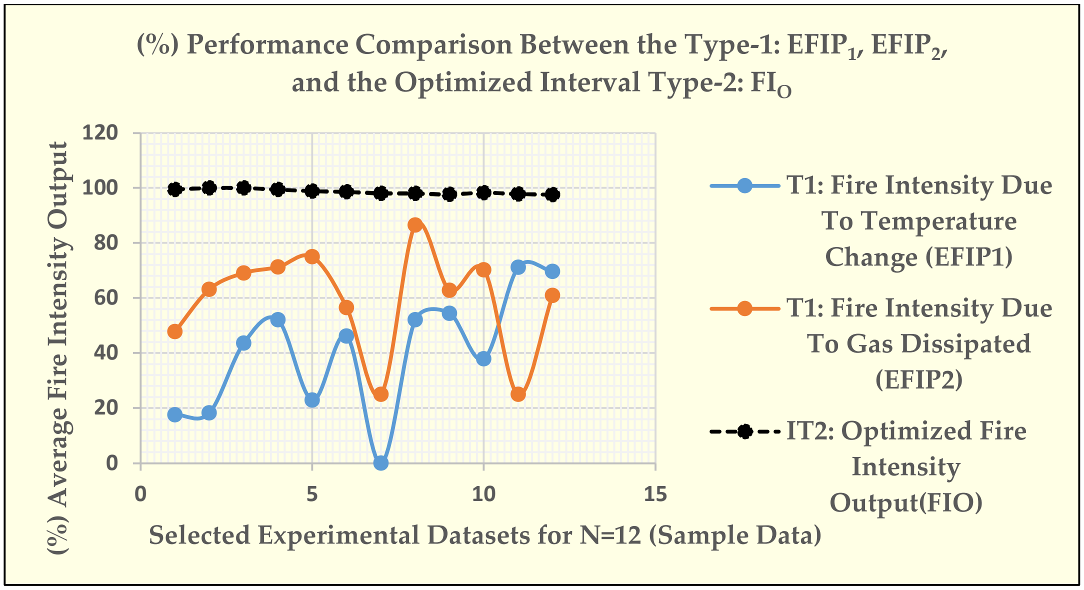


Fig. 4.11: Performance Comparison of Mamdani's Type-1 Fuzzy Models (EFIP_1, EFIP_2) and the Proposed Interval Type-2 TSK Output ($\widetilde{\mathrm{FI}}_{\mathrm{O}}$).

From the Expt., Fig.4.10, defines a set of absolute dataset values extracted to study the correction between of $\widetilde{\mathrm{FI}}_{\mathrm{T}}$, $\widetilde{\mathrm{FI}}_{\mathrm{G}}$ with respect to the output $\left(\widetilde{\mathrm{FI}}_{\mathrm{O}}\right)$ of proposed IT2 TSK model. The firing strength of the output is computed as per the sparse inference rules. A smooth stable curve (dash-line) of optimized fire intensity $\left(\widetilde{\mathrm{FI}}_{\mathrm{O}}\right)$, is obtained, giving higher output of 98.2% with Enhanced Karnik-Mendel (eKM) TR algorithm. Hence, heat transferred during combustion increases with $\left(\widetilde{\mathrm{FI}}_{\mathrm{O}}\right)$ of the model. The outcome 98.2% is computed as better fit data using regression analysis. Thus, a significant improvement in output of $\left(\widetilde{\mathrm{FI}}_{\mathrm{O}}\right)$ is realized using IT2 TSK fuzzy inference system compared to Mamdani T1 in E. Lule et al.,[2]. Also, a sudden drop (unstable state) is observed through $\widetilde{\mathrm{FI}}_{\mathrm{T}} = 0.7959$ to 0.02041, $\widetilde{\mathrm{FI}}_{\mathrm{G}} = 1$ to $\mathbf{0.1429}$. Because of the uncertainty errors derived from rule consequents in the model design. Secondly, reduced oxygen levels depleted to support combustion, reflect a drop in output. Thus, results show a subsequent further drop in both temperature and gas concentration to the surrounding atmosphere.

4.9.3 Evaluation of the Interval Type-2 TSK Model Using Regression Analysis

Three different Expt. datasets (X, Y and Z) shown below, are successfully extracted from the proposed IT2 TSK simulated fuzzy model in range of [1, -1]. From the datasets, we determine the best fit choice of data for the model using the statistical regression analysis method. Regression analysis is useful for identifying the data that has the greatest influence on the proposed IT2 TSK model. A correlation between the independent observed input variables of $\widetilde{\mathbf{FI}}_{\mathbf{T}}$ and,$\widetilde{\mathbf{FI}}_{\mathbf{G}}$, and the dependent output variable $\left(\widetilde{\mathbf{FI}}_{\mathbf{O}}\right)$ and the expected outcome (**E**) is determined. The best fit linear regression equations are determined for the various datasets (X, Y and Z) as: $\boldsymbol{y = -0.2281x + 0.5215; y = 0.0802x + 0.3763; and\ y = -0.3025 + 0.8382}$ respectively.

R^2 is the coefficient of determination around the fitted regression line: Error parameters are used to determine the discrepancies such as; MAE, MSE and RMSE. Then, a corresponding expected outcome E is computed. Expt. X has the least value of RMSE = 1.3015. Hence, this qualifies "Experimental Dataset X", as the best fit data for the proposed IT2 TSK fuzzy model, with average accuracy outcome of 98.2% determined. The error metric measures (ref. Eqns. 4.15 - 4.17), i.e., Mean Absolute Error (**MAE)**, Mean Square Error (**MSE)** and Root Mean Square Error (**RMSE)** are then used to compute the error discrepancy for the model output data, mathematically defined as;

4.9.4 Derived Extracted Experimental Datasets (X, Y and Z)

Expt. No.	**FI_T**	**FI_G**	**FI_O**	**Expected, E**	**FI_O -E**	**$\|FI_O$ -E$\|$**	**$\|FI_O$ -E$\|^2$**
1	0.4286	0.1020	-0.9958	0.4237	-1.4195	1.4195	2.0151
2	0.2653	-0.1429	-1.0000	0.3020	-1.3020	1.3020	1.6952
3	0.7143	-1.0000	-1.0000	0.3206	-1.3206	1.3206	1.7441
4	0.7143	0.1429	-0.9943	0.3206	-1.3149	1.3149	1.7291
5	0.8367	0.2653	-0.9895	0.3257	-1.3152	1.3152	1.7298
6	0.7551	0.3469	-0.9864	0.3223	-1.3087	1.3087	1.7128
7	0.7959	0.4694	-0.9818	0.3240	-1.3058	1.3058	1.7052
8	0.1837	0.5102	-0.9804	0.2986	-1.2790	1.2790	1.6359
9	-0.0204	0.5918	-0.9774	0.2902	-1.2676	1.2676	1.6067
10	0.3061	0.4286	-0.9834	0.3037	-1.2871	1.2871	1.6566
11	0.2653	0.5510	-0.9788	0.3020	-1.2808	1.2808	1.6405
12	0.4286	0.6327	-0.9758	0.3088	-1.2846	1.2846	1.6502
13	0.3878	0.7959	-0.9700	0.3071	-1.2771	1.2771	1.6310
14	0.3061	1.0000	-0.9629	0.3037	-1.2666	1.2666	1.6043
15	0.8367	0.9184	-0.9656	0.3257	-1.2913	1.2913	1.6675
16	0.8776	0.7551	-0.9713	0.3274	-1.2987	1.2987	1.6867
17	0.6327	0.5102	-0.9803	0.3173	-1.2976	1.2976	1.6837

Expt. X: Experimental **Dataset X**

Expt. No.	**FI_T**	**FI_G**	**FI_O**	**Expected, E**	**FI_O -E**	**$\|FI_O$ -E$\|$**	**$\|FI_O$ -E$\|^2$**
1	-0.7143	0.9184	-0.9656	0.3190	-1.2846	1.2846	1.6502
2	-0.3469	0.7959	-0.9700	0.3485	-1.3185	1.3185	1.7384
3	-0.6327	0.7143	-0.9728	0.3256	-1.2984	1.2984	1.6857
4	-0.0204	0.8779	-0.9672	0.3747	-1.3419	1.3419	1.8006
5	0.0612	0.7959	-0.9701	0.3812	-1.3513	1.3513	1.8260
6	0.5510	0.8776	-0.9671	0.4205	-1.3876	1.3876	1.9254
7	0.3878	0.6327	-0.9758	0.4074	-1.3832	1.3832	1.9132
8	0.1837	0.5102	-0.9804	0.3910	-1.3714	1.3714	1.8808
9	-0.4286	0.3878	-0.9849	0.3419	-1.3268	1.3268	1.7605
10	-0.1020	0.2653	-0.9896	0.3681	-1.3577	1.3577	1.8434
11	-0.5102	0.1837	-0.9927	0.3354	-1.3281	1.3281	1.7638
12	-0.1837	0.1020	-0.9959	0.3616	-1.3575	1.3575	1.8427
13	0.1429	-0.0612	-1.0000	0.3878	-1.3878	1.3878	1.9259
14	-0.4286	-0.2245	-1.0000	0.3419	-1.3419	1.3419	1.8008
15	-0.5102	-0.7551	-1.0000	0.3354	-1.3354	1.3354	1.7832
16	0.5918	0.0612	-0.9976	0.4238	-1.4214	1.4214	2.0203
17	0.8367	0.2245	-0.9911	0.4434	-1.4345	1.4345	2.0578

Expt. Y: Experimental **Dataset Y**

Expt. No.	FI_T	FI_G	FI_O	Expected, E	FI_O -E	$\|FI_O$ -E$\|$	$\|FI_O$ -E$\|^2$
1	0.9184	0.3061	-0.9880	0.5604	-1.5484	1.5484	2.3975
2	0.9184	0.3469	-0.9864	0.5604	-1.5468	1.5468	2.3925
3	0.7551	0.4286	-0.9833	0.6098	-1.5931	1.5931	2.5379
4	0.8367	0.5510	-0.9788	0.5851	-1.5639	1.5639	2.4458
5	0.8367	0.6327	-0.9758	0.5851	-1.5609	1.5609	2.4364
6	0.7959	0.7143	-0.9728	0.5974	-1.5702	1.5702	2.4657
7	0.6327	0.7551	-0.9714	0.6468	-1.6182	1.6182	2.6186
8	0.6735	0.8367	-0.9685	0.6345	-1.6030	1.6030	2.5695
9	0.2653	0.8776	-0.9671	0.7579	-1.7250	1.7250	2.9758
10	0.5918	0.8776	-0.9671	0.6592	-1.6263	1.6263	2.6448
11	0.7551	0.9184	-0.9656	0.6098	-1.5754	1.5754	2.4818
12	0.3878	0.9592	-0.9643	0.7209	-1.6852	1.6852	2.8399
13	-0.1429	0.9529	-0.9643	0.8814	-1.8457	1.8457	3.4067
14	0.4694	0.7551	-0.9714	0.6962	-1.6676	1.6676	2.7809
15	0.4286	0.5510	-0.9788	0.7085	-1.6873	1.6873	2.8471
16	0.5918	0.4286	-0.9833	0.6592	-1.6425	1.6425	2.6977
17	0.1020	0.3878	-0.9849	0.8073	-1.7922	1.7922	3.2121

Expt. Z: Experimental **Dataset Z**

i. **MAE** = $\sum \frac{|FI_0 - E|}{N}$ (4.15)

ii. **MSE** = $\sum \frac{|FI_0 - E|^2}{N}$ (4.16)

iii. **RMSE** = $\sqrt{\sum \frac{|FI_0 - E|^2}{N}}$ **or** $\sqrt{MSE}$ (4.17), For N =17, sampled fuzzy based sparse inference rule outcomes.

Expt. Datasets (X, Y, Z)	MAE	MSE	RMSE	R^2	Av. Accuracy Outcome	For N =17 Sample rule Outcomes
Expt. X	**1.3010**	**1.6938**	**1.3015**	**0.0180**	**98.2%**	√
Expt. Y	1.3546	1.8364	1.3551	0.0065	98.4%	X
Expt. Z	1.6383	2.6912	1.6405	0.1570	97.5%	X

Table 4.9: Summary of the Statistical Measured Parameters of MAE, MSE, R^2 and RMSE

4.9.5 Performance Comparison Between the Related Works and Proposed Solution.

	Zulkarnain *at el.*[82] (**2021**)	Lule *at el.* (**2020**)[2]	Renzo *at* el.[83] (**2020**)	Pu Li *at el.* [84](**2020**)	Sawar *at el.*[85] (**2019**)	Proposed IT2 TSK Fuzzy Model Solution
Accuracy Rate	90%	95.8%	91%	83%	95%	98.2%
Method or Techniques Used	Uses Fuzzy Application Methods	TI Mamdani's Fuzzy Systems	TI Fuzzy Control Systems	Using CNN models	Conventional T1 Fuzzy systems.	Interval Type-2 TSK Fuzzy Control Systems
Application Domain	Early Detection of Fire in the Wetlands Using Fuzzy Methods, in Indonesia	Fire Detection Model Using Fuzzy Based Approximation applied in Local Urban Markets.	Dissolved Gas Analysis (DGA) for Identifying Fault Failures in Power Transformers.	Image Fire Detection Algorithm based on CNN Models.	Intelligent Fire Warning System for Smart Buildings (FMWS).	Proposed Intelligent Lightweight Fire Intensity Detection Algorithm for Low-Cost Fire Detection Devices.

Table 4.8: Performance Comparison Between the Proposed IT2 TSK Fuzzy Model and Previous Related Works.

4.9.6 Conclusion and Future Works

The study presents a novel idea of a lightweight fire intensity detection algorithm with decision-making in low-power devices was presented in the study using an interval Type-2 TSK fuzzy control model. We demonstrate that by boosting accuracy to 98.2% with MAE = 1.3010, MSE = 1.6938, and RMSE = 1.3015, the suggested IT2 TSK fuzzy model significantly reduced the uncertainty-bound errors associated with Type-1 fuzzy logic system (FLS). The Interval Type-2 fuzzy logic system reduces the uncertainty errors inherent in the Type-1 fuzzy system by providing an additional degree of freedom known as footprint of uncertainty (FOU) in its fuzzy sets [27]. The IT2 TSK fuzzy technique can be used in conjunction with the proposed solution to improve sensitivity and minimize false alerts in low-cost, low-power fire detection systems. Alternately, a more precise model can be developed with adaptive neural fuzzy inference systems (ANFIS). The TSK inference system, which combines computational intelligence and fuzzy logic to provide precise model learning capabilities, is the foundation of the ANFIS technique. Future development includes creating a low-cost, hardware-based fire detection system that makes use of fuzzy application techniques. The technique improves market community protection and future fire safety management through early warning notifications for safety evacuations. The study serves as the foundation for the development of integrated low-power fire detection systems that are affordable and simple for firefighting personnel to install in developing nations with the intention of safeguarding urban markets and public areas from fire accidents.

CHAPTER 5

HARDWARE IMPLEMENTATION OF AN IoT-BASED FIRE DETECTION SYSTEM PROTOTYPE USING FUZZY APPLICATION METHODS

Chapter 5 was developed based on the following article: Lule, E., Mikeka, C., Ngenzi, A., Mukanyiligira, D., Musdalifah, P. (2024). Hardware Design and Implementation of a Low-Cost IoT-Based Fire Detection System Prototype Using Fuzzy Application Methods. In: Silhavy, R., Silhavy, P. (eds) Data Analytics in System Engineering. CoMeSySo 2023. Lecture Notes in Networks and Systems, vol 910. Springer, Cham. https://doi.org/10.1007/978-3-031-53552-9_6

5.1 Introduction

Local urban markets that are centrally located within the metropolitan areas of Uganda continually face a recurrent problem of fire accidents. For instance, St. Balikudembe (Owino) and Kiseka markets. The major cause of these market fire outbreaks is attributed to electrical circuits, suspected arson, neglected charcoal stoves, and negligence [3][2][4]. Based on our findings, we conclude that little or no effort has been made to ensure adequate control and suppression of these wildfires in order to ensure the safety and protection of nearby communities. In addition, several properties worth millions of shillings have been lost due to uncontrolled fire outbreaks within the market communities resulting from delayed signaling. For example, in Fig. 5.1, we show the number of victims affected by fire accidents ranging from 2012 to 2020, including both injured and fatal victims [6][5].

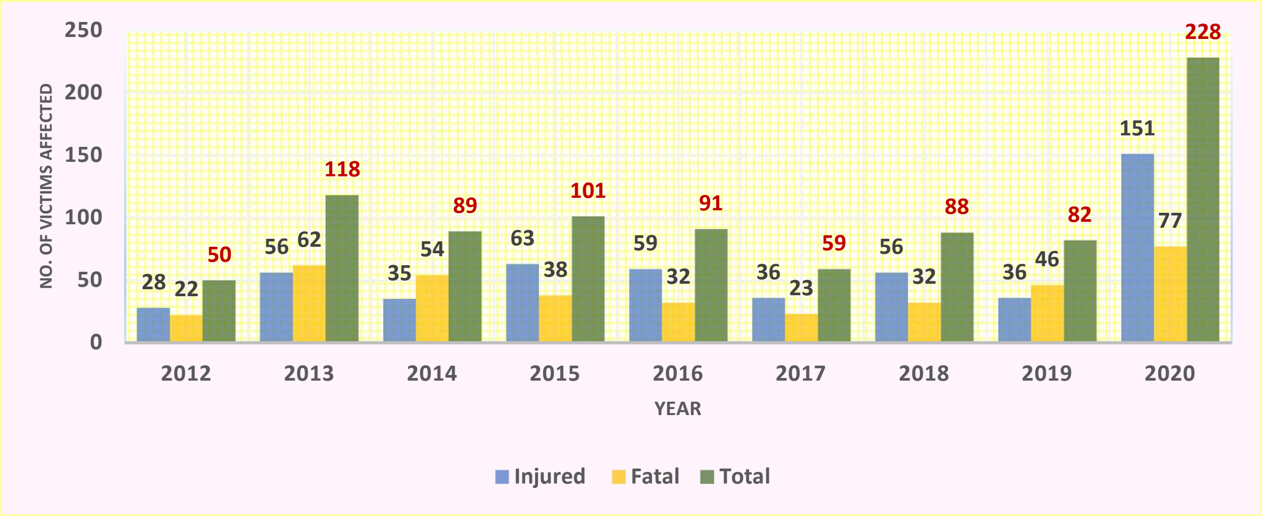


Fig. 5.1: Report on the Victims affected by Fire Accidents in Uganda: Injured, Fatal and Total No. of Victims Between the Period of (2012-2020)[4].

Source: Uganda Police Force (UPF) Reports (2012-2020), Under the Dept. of Fire and Rescue Services Department, Uganda[4].

Single sensor smoke detectors for effective fire monitoring, on the other hand, are highly prone to false alarms due to high sensitivity calibration [86][87][46]. Similarly, satellite systems are prohibitively expensive to acquire and maintain in LDCs[88][8][89]. With current advancements in IoT technology, intelligent and low-cost fire detection systems based on fuzzy logic can be developed for easy deployment in markets or building premises to effectively minimize fire accidents and ensure safe evacuation through public community protection [4][5]. IoT is thus engaged by collecting related fire data and then making an informed decision for future predictions using fuzzy based algorithms. This study proposes an IoT-enabled, low-cost hardware fire detection system using fuzzy application methods with the aim of safeguarding the community by providing early warning notification signals for quick and safe evacuation of persons. Hence, the proposed hardware solution employs a multisensory approach to compensate for erroneous false alarms by instigating true alarm warnings of a fire outbreak and compelling authorities to respond immediately.

5.2 Fuzzy Application Methods

Fuzzy logic is a soft computing approach based on "degrees of truth" rather than the traditional "true" or "false", also represented as 0 or 1, expressions that are the foundation of modern computing. Loft Zadeh of the University of California, Berkely [90] invented fuzzy logic. When combined with artificial intelligence (AI), fuzzy logic can simulate human reasoning and cognition for intelligent decision-making. Hence, intelligent engineering and computation decisions can be made with clear certainties and uncertainties when using imprecise datasets in natural language processing or regulating and controlling machine inputs [91][92]. This study represents the corresponding membership functions of the proposed low-cost fire detection system using mathematical expressions in the form of fuzzy sets with triangular functions. Therefore, we represent fuzzy systems mathematically using triangular membership function (trimf) mathematical computation. Mathematical computation and representation of "*fuzzy sets*" in engineering systems technology

Using temperature and CO_2 as the primary input parameters for the proposed fire detection system, we used the fuzzy logic technique to make an informed "fire status" decision. The "fuzzification" method converts crisp inputs into fuzzy values using a defined knowledge base (cf. Fig. 5.2e) [93][94][4][19]. Thus, the fuzzy membership values for the ΔT and CO_2 input parameters are as follows: ΔT = {Low, Moderate, High}; ΔCO_2 = {Very Low, Low, Moderate, High, Very High}. The process of converting output fuzzy sets back to single, crisp number logic is known as "defuzzification." The output fire intensity (FI) is then converted into a fuzzy range [0, 1], which represents the rate of heat transfer per unit time. As a result, FI = {VL, L, M, H, and VH}. To minimize the computational overload associated with fuzzy logic design, the proposed hardware prototype utilized five sparse fuzzy inference rules (FIS) as follows:

1. IF temp is **Low** AND CO_2 is **Very Low** THEN FI is **VL**
2. IF temp is **Low** AND CO_2 is **Low** THEN FI is **L**
3. IF temp is **Moderate** AND CO_2 is **Moderate** THEN FI is **M**
4. IF temp is **High** AND CO_2 is **High** THEN FI is **H**
5. IF temp is **High** AND CO_2 is **Very High** THEN FI is **VH**

The FIS design produces a crisp output after "***defuzzification***." The output is obtained by using the "***Centroid***" defuzzification method, which finds the center of the area of fuzzy sets and returns the associated crisp value [20][6]. Fig. 5.2(a-b) depicts the derived fuzzy set membership function (MF) information for input parameters: Temperature, and Carbon dioxide (CO_2), as well as the output parameter fuzzy set (Fig. 5.2c) known as; "Fire Index" or "Fire Intensity (FI)":

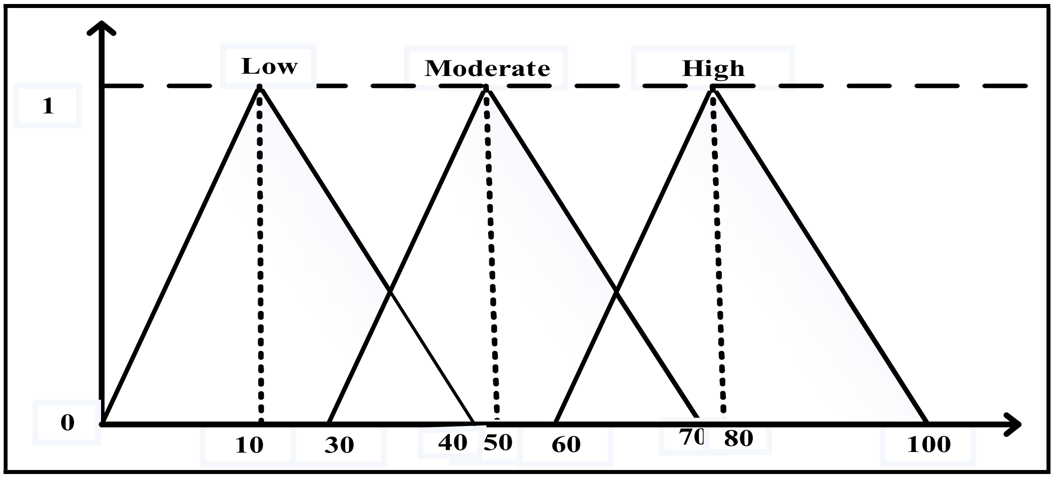


Fig. 5.2a: Temperature (as Input) MF Fuzzy Set Variations[90].

Derived mathematical fuzzy membership functions (MF) of element x in set X, the degree of membership μX [x] to the unit interval [0-1] in Fig. 5.2a, for input temperature using the triangular MF can be explicitly defined using the fuzzy set equations from Eqns. (5.1– 5.3) below:

$$\mu\text{Low}[x] = \begin{cases} 1, & x \leq 0 \\ \frac{x-0}{20-0}, & 0 \leq x \leq 20 \\ \frac{40-x}{40-20}, & 20 \leq x \leq 40 \\ 0, & 40 \leq x \end{cases} \tag{5.1}$$

$$\mu\text{Moderate}[x] = \begin{cases} 1, & x \leq 30 \\ \frac{x-30}{50-30}, & 30 \leq x \leq 50 \\ \frac{70-x}{70-50}, & 50 \leq x \leq 70 \\ 0, & 70 \leq x \end{cases} \tag{5.2}$$

$$\mu\text{High}[x] = \begin{cases} 1, & x \leq 60 \\ \frac{x-60}{80-60}, & 60 \leq x \leq 80 \\ \frac{100-x}{100-80}, & 80 \leq x \leq 100 \\ 0, & 100 \leq x \end{cases} \tag{5.3}$$

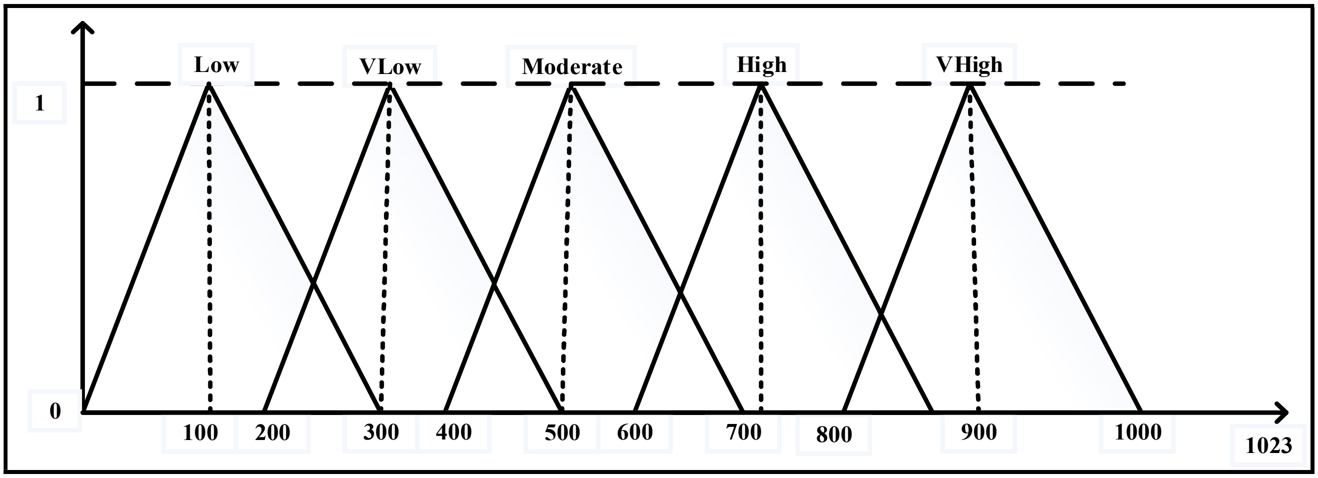


Fig. 5.2b: Carbon dioxide (as Input) MF Fuzzy Set Variations[90].

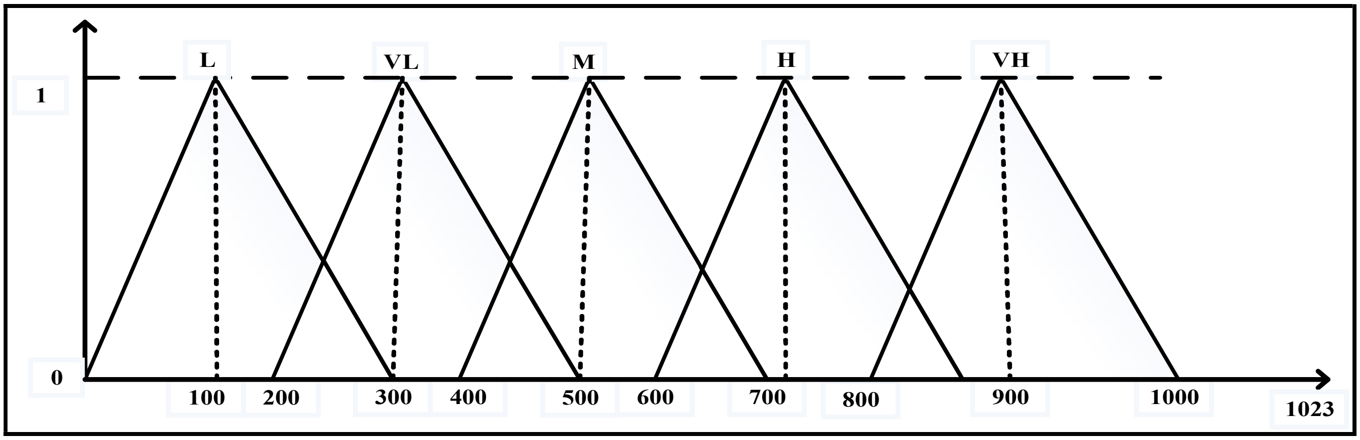


Fig. 5.2c: Flame Intensity (FI), (as Output) MF Fuzzy Set Variations[90].

The membership functions for carbon dioxide in correlation with fire intensity can be implicitly represented in the same manner as follows per the Eqns. (5.4-5.8).

$$\mu\text{Vlow }[x] \text{ or } \mu\text{VL}[x] = \begin{cases} 1, & x \le 0 \\ \frac{x-100}{100-0}, & 0 \le x \le 100 \\ \frac{300-x}{300-100}, & 100 \le x \le 300 \\ 0, & 300 \le x \end{cases} \tag{5.4}$$

$$\mu\text{Low }[x] \text{ or } \mu\text{L}[x] = \begin{cases} 1, & x \le 200 \\ \frac{x-200}{300-200}, & 200 \le x \le 300 \\ \frac{400-x}{400-300}, & 300 \le x \le 400 \\ 0, & 400 \le x \end{cases} \tag{5.5}$$

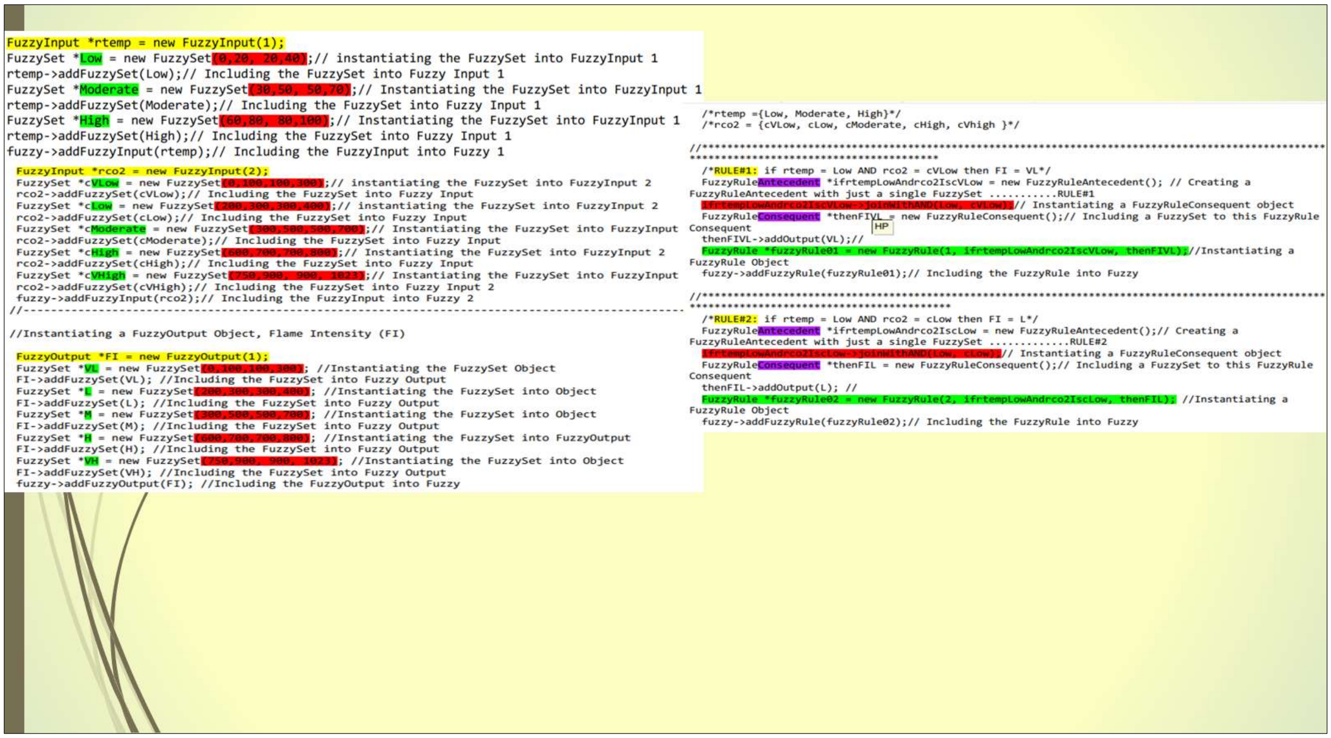
$$\mu\text{Moderate }[x] \text{ or } \mu\text{M}[x] = \begin{cases} 1, & x \le 300 \\ \frac{x-300}{500-300}, & 300 \le x \le 500 \\ \frac{700-x}{700-500}, & 500 \le x \le 700 \\ 0, & 700 \le x \end{cases} \tag{5.6}$$

$$\mu\text{High}\ [x] \text{ or } \mu\text{H}[x] = \begin{cases} 1, & x \leq 600 \\ \dfrac{x-600}{700-600}, & 600 \leq x \leq 700 \\ \dfrac{800-x}{800-700}, & 700 \leq x \leq 800 \\ 0, & 800 \leq x \end{cases} \tag{5.7}$$

$$\mu\text{VHigh}\ [x] \text{ or } \mu\text{VH}[x] = \begin{cases} 1, & x \leq 750 \\ \dfrac{x-750}{900-750}, & 750 \leq x \leq 900 \\ \dfrac{1023-x}{1023-900}, & 900 \leq x \leq 1023 \\ 0, & 1023 \leq x \end{cases} \tag{5.8}$$

5.3 Implementation of the Proposed Sparse Fuzzy Inference Rules (FIR) within the Arduino Integrated Development Environment (IDE)

Fig. 5.2d illustrates how the sparse-based rule implementation is integrated within the Arduino IDE for optimal operations. The header file #**include<Fuzzy.h>** contains the implementation standards of all fuzzy rules operations as a requirement for the embedded fuzzy logic library (eFLL);



```
FuzzyInput *rtemp = new FuzzyInput(1);
FuzzySet *Low = new FuzzySet(0,20, 20,40);// instantiating the FuzzySet into FuzzyInput 1
rtemp->addFuzzySet(Low);// Including the FuzzySet into Fuzzy Input 1
FuzzySet *Moderate = new FuzzySet(30,50, 50,70);// Instantiating the FuzzySet into FuzzyInput 1
rtemp->addFuzzySet(Moderate);// Including the FuzzySet into Fuzzy Input 1
FuzzySet *High = new FuzzySet(60,80, 80,100);// Instantiating the FuzzySet into FuzzyInput 1
rtemp->addFuzzySet(High);// Including the FuzzySet into Fuzzy Input 1
fuzzy->addFuzzyInput(rtemp);// Including the FuzzyInput into Fuzzy 1
 FuzzyInput *rco2 = new FuzzyInput(2);
 FuzzySet *cVLow = new FuzzySet(0,100,100,300);// instantiating the FuzzySet into FuzzyInput 2
 rco2->addFuzzySet(cVLow);// Including the FuzzySet into Fuzzy Input
 FuzzySet *cLow = new FuzzySet(200,300,300,400);// instantiating the FuzzySet into FuzzyInput 2
 rco2->addFuzzySet(cLow);// Including the FuzzySet into Fuzzy Input
 FuzzySet *cModerate = new FuzzySet(300,500,500,700);// Instantiating the FuzzySet into FuzzyInput
 rco2->addFuzzySet(cModerate);// Including the FuzzySet into Fuzzy Input
 FuzzySet *cHigh = new FuzzySet(600,700,700,800);// Instantiating the FuzzySet into FuzzyInput 2
 rco2->addFuzzySet(cHigh);// Including the FuzzySet into Fuzzy Input
 FuzzySet *cVHigh = new FuzzySet(750,900, 900, 1023);// Instantiating the FuzzySet into FuzzyInput
 rco2->addFuzzySet(cVHigh);// Including the FuzzySet into Fuzzy Input 2
 fuzzy->addFuzzyInput(rco2);// Including the FuzzyInput into Fuzzy 2
//-----------------------------------------------------------------------------------------

//Instantiating a FuzzyOutput Object, Flame Intensity (FI)

 FuzzyOutput *FI = new FuzzyOutput(1);
 FuzzySet *VL = new FuzzySet(0,100,100,300); //Instantiating the FuzzySet Object
 FI->addFuzzySet(VL); //Including the FuzzySet into Fuzzy Output
 FuzzySet *L = new FuzzySet(200,300,300,400); //Instantiating the FuzzySet into Object
 FI->addFuzzySet(L); //Including the FuzzySet into Fuzzy Output
 FuzzySet *M = new FuzzySet(300,500,500,700); //Instantiating the FuzzySet into Object
 FI->addFuzzySet(M); //Including the FuzzySet into Fuzzy Output
 FuzzySet *H = new FuzzySet(600,700,700,800); //Instantiating the FuzzySet into FuzzyOutput
 FI->addFuzzySet(H); //Including the FuzzySet into Fuzzy Output
 FuzzySet *VH = new FuzzySet(750,900, 900, 1023); //Instantiating the FuzzySet into Object
 FI->addFuzzySet(VH); //Including the FuzzySet into Fuzzy Output
 fuzzy->addFuzzyOutput(FI); //Including the FuzzyOutput into Fuzzy
```

```
  /*rtemp ={Low, Moderate, High}*/
  /*rco2 = {cVLow, cLow, cModerate, cHigh, cVhigh }*/

//**************************************************************************************************
****************************************
  /*RULE#1: if rtemp = Low AND rco2 = cVLow then FI = VL*/
  FuzzyRuleAntecedent *ifrtempLowAndrco2IscVLow = new FuzzyRuleAntecedent(); // Creating a
FuzzyRuleAntecedent with just a single FuzzySet ..........RULE#1
  ifrtempLowAndrco2IscVLow->joinWithAND(Low, cVLow);// Instantiating a FuzzyRuleConsequent object
  FuzzyRuleConsequent *thenFIVL = new FuzzyRuleConsequent();// Including a FuzzySet to this FuzzyRule
Consequent
  thenFIVL->addOutput(VL);//
  FuzzyRule *fuzzyRule01 = new FuzzyRule(1, ifrtempLowAndrco2IscVLow, thenFIVL);//Instantiating a
FuzzyRule Object
  fuzzy->addFuzzyRule(fuzzyRule01);// Including the FuzzyRule into Fuzzy

//**************************************************************************************************
****************************************
  /*RULE#2: if rtemp = Low AND rco2 = cLow then FI = L*/
  FuzzyRuleAntecedent *ifrtempLowAndrco2IscLow = new FuzzyRuleAntecedent();// Creating a
FuzzyRuleAntecedent with just a single FuzzySet ............RULE#2
  ifrtempLowAndrco2IscLow->joinWithAND(Low, cLow);// Instantiating a FuzzyRuleConsequent object
  FuzzyRuleConsequent *thenFIL = new FuzzyRuleConsequent();// Including a FuzzySet to this FuzzyRule
Consequent
  thenFIL->addOutput(L); //
  FuzzyRule *fuzzyRule02 = new FuzzyRule(2, ifrtempLowAndrco2IscLow, thenFIL); //Instantiating a
FuzzyRule Object
  fuzzy->addFuzzyRule(fuzzyRule02);// Including the FuzzyRule into Fuzzy
```

Fig. 5.2d: Fuzzy sets and Fuzzy Inference Rule (FIR) Implementation Using the Arduino Integrated Development Environment (IDE) ver. 1.8.15

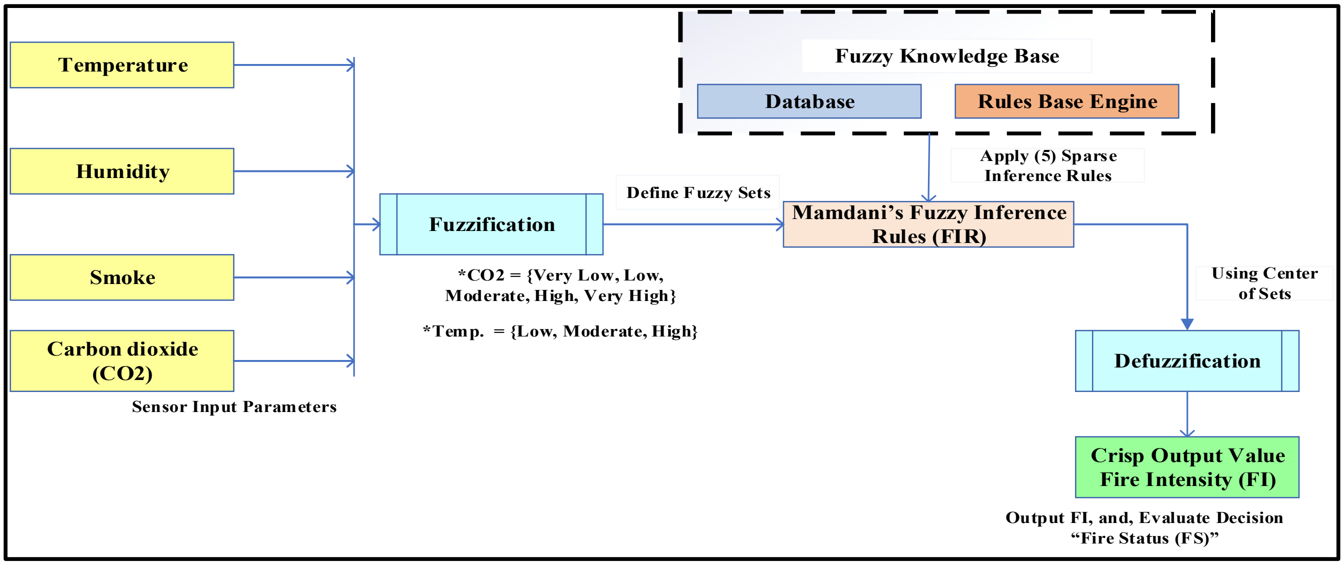


Fig. 5.2e: Proposed Fuzzy Based Controller for the Low-Cost Hardware IoT-Based Fire Detection Prototype.

5.4 The Architectural Overview of the Proposed Fire Detection Prototype

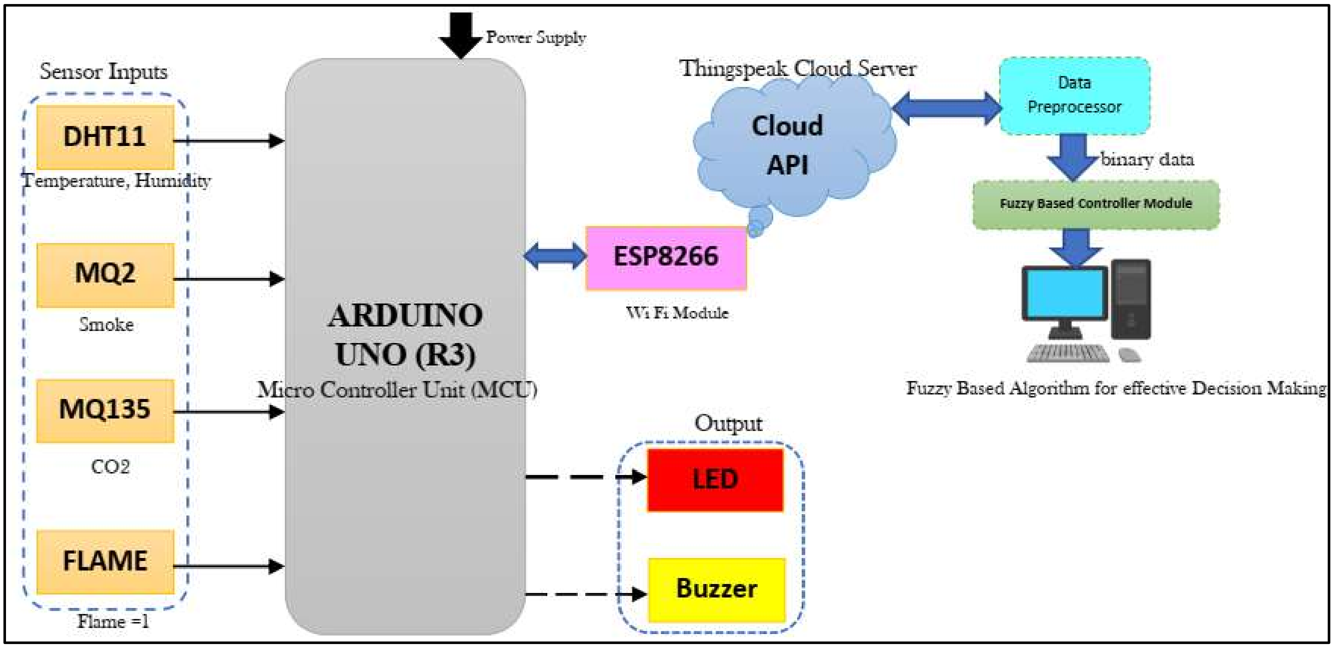


Fig. 5.3. The Architectural Design Overview of the Proposed Fuzzy Based Fire Detection System.

Figure 5.3 depicts the architectural design overview of the proposed hardware prototype of an IoT enabled fire detection system. The sensor components, DHT11, MQ2, MQ135 and Flame (LM-393). Sensor modules, were interfaced with the Arduino Uno microcontroller unit (MCU) to collect the fire data. The sensors gather related data on *temperature, humidity*, *CO_2*, *smoke*, and *flame*. The ESP8266 Wi-Fi module then sends data to an open-source Thing Speak cloud Application Programming Interface (API) platform for analysis and storage as a "***.csv**" file, which is equivalent to a data preprocessor. Buzzer and LED actuator modules are linked together to alert authorities in the event of a fire outbreak via sound alarm (for buzzer) and a light warning signal (for LED).

To make an informed decision, ΔT and CO_2 generated datasets are analyzed and evaluated using the fuzzy method to give a fire status condition of the surrounding area. The proposed fuzzy logic controller for the fire detection system prototype is shown in Fig. 5.2e. The major parameters to be fuzzified are temperature owing to combustion defined as; temperature (ΔT) and gas dissipated (CO_2) due to complete combustion, where; CO_2 = {VLow, Low, Moderate, High, VHigh}; and Temperature(ΔT) = {Low, Moderate, High}; (**cf.** Fig. 5.2(a-b). Hence, the fire detection systems prototype employs a fuzzy knowledge base comprised of the determined inference sparse rules (Fig. 5.2e). A defuzzification process is then used to determine the system's crisp output called the "Fire Intensity or Index (FI)". For which the fuzzy membership values of fire intensity determined as FI = {VL, L, M, H, and VH} (Fig. 5.2c).

5.5 Schematic Circuit Design of the Proposed Fire Detection Systems Prototype

Fig. 5.4, shows a schematic design and circuit design overview of the proposed hardware fire detection system. Fritzing software was used to design the circuit connection (ver. 0.9.3b). This is a free and open software platform for designing printed circuit boards (PCBs) before they are built. The proposed circuit was not fabricated but simply implemented using sensor modules. The sensor modules MQ2, MQ135, DHT11, Flame (KY-026 or LM-393), and ESP8266 Wi-Fi Module are used in the circuit design. Table 5.1 shows a detailed description and purpose for using each of the sensor modules mentioned.

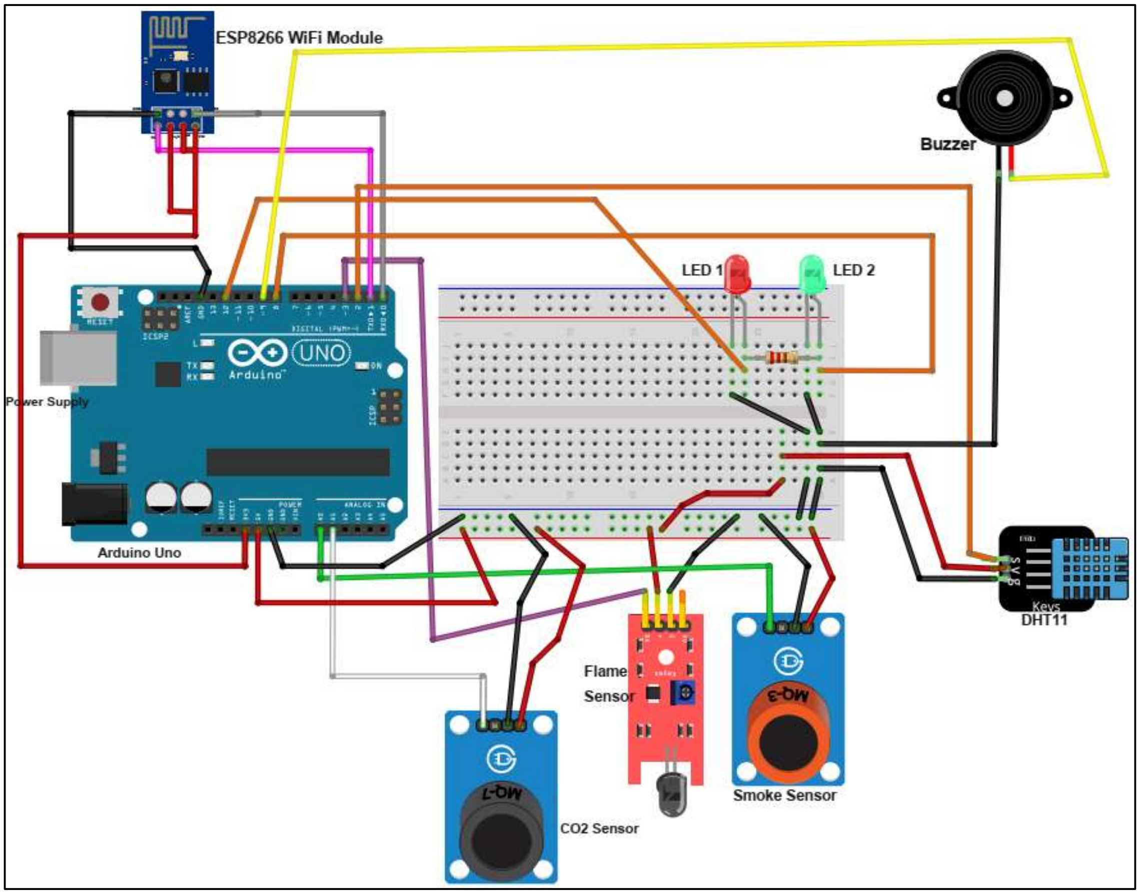


Fig. 5.4: Schematic Diagram of the Proposed Fire Detection System Prototype Using the Fritzing Software (Version 0.9.3b).

Fig. 5.4 illustrates the detailed schematic design circuit overview of the proposed hardware IoT-enabled fire detection system. In this study, Fritzing software (ver. 0.9.3b) was used to design the circuit connection by interfacing various sensor components to the Arduino Uno (MCU) board. Fritzing is a free and open-source software platform for designing and prototyping printed electronic circuit boards (PCB) before they are built or implemented. Various sensor modules, namely the MQ2, MQ135, DHT11, (LM 393 or KY-026) and ESP8266 Wi-Fi Module, have been used in the design of the hardware fire detection prototype circuit. In Section 5.6, a detailed description of the hardware components required, measured parameters, and purpose for using each of the sensor modules mentioned in the schematic design circuit is given in Fig. 5.4.

5.6 Hardware and Software Requirements for Implementation of the Proposed Fire Detection Prototype

The study considered an experimental hardware fire detection system prototype using fuzzy application methods. The prototype consisted of an embedded system Arduino UNO board integrated with the Arduino integrated development environment (IDE) software (Ver. 1.8.15). Various sensors are interfaced with the Arduino UNO through the breadboard. Sensor modules, i.e., DHT11: for temperature and humidity, MQ2; for smoke detection, MQ135; for detecting CO_2 dissipated in the atmosphere due to a fire outbreak. The flame sensor detects infrared (IR) flames with configurations of KY-026, or LM 393. If flame = 0, "fire is detected" or flame = 1, "no fire". The Expt. is interfaced with the actuator sensors, i.e., a buzzer for alarm signaling when fire is detected and an LED for light signaling when fire is detected. The "Red-LED" represents fire detected, and the "Green-LED" represents smoke detected. Then, the ESP8266 module provides internet communication to send all the collected data to the Thing Speak cloud API for insightful analysis purposes

5.6.1 Hardware Requirement

Hardware	Parameters	Purpose
Flame Sensor (LM393)	Flame Presence	Detects IR Flames
MQ2	Smoke	Detects presence of Smoke
MQ135	CO_2	Detects Presence of CO_2
ESP 8266 Wi-Fi Module	Provides Internet Connection through the MQTT protocol	To send data to the cloud API via Internet.
LED	For Light Signaling	Provides Light Warning
Piezo Buzzer		Provides Sound Signal
Resistor	1-2 K-Ohms	To drop the Vcc current not required to operate the LED.
DHT11	Temperature, Humidity	Temperature, Humidity.

Table 5.1: Hardware Requirements of the Proposed Fire Detection Systems Prototype.

5.6.2 Software Requirements

Software	Purpose
Fritzing Software (Ver. 0.9.3b)	Designing of electronic circuits before production
Arduino IDE Version (1.8.13)	Provides a programming environment for the development of embedded sensor systems hardware devices.
Thing Speak Cloud API	IoT Cloud server platform for data storage and analysis.
MATLAB Visualization Tool	MATLAB Tool Embedded and Integrated within the Thing Speak Cloud API

Table 5.2: Software Requirements Used in Design and Implementation Fire Detection Prototype.

In Table 5.3, we describe the major sensor pin name configurations used in the experimental design of the proposed fire detection system. Their respective purpose or significance description is defined as per Table 5.3 below.

Pin Name	Description
GND or (-)	Ground Pin
A0	Analog Output Pin
D0	Digital Output Pin
Vcc or (+)	Power Supply
DATA	Data Pin
Vin	Voltage in Pin
RX	Receive Pin
TX	Transmission Pin
RESET	Reset Button
PWM	Pulse Width Modulation

Table 5.3: Shows the Detailed Major Sensor Pin Configuration Used in the Proposed Fire Detection Prototype Experiment.

5.6.2 Proposed Framework of the Low-Cost Fire Detection System Prototype.

The framework flowchart in (cf. Fig. 5.5), below, depicts the operation of the fire detection prototype. As inputs, the solution accepts temperature, humidity, smoke, CO_2, and flame parameters. If an infrared (IR) flame is detected, fire has been detected. A signal notification is sent to authorities to alert them that "fire has been detected." When smoke is detected, authorities are also notified. Data is collected and sent to the Thing Speak cloud for storage and analysis in order to gain insights. The fuzzy method is then applied to dissipated gas, namely CO_2, and temperature (ΔT), as primary factors contributing to a fire outbreak detected by certain deviations from normal. We obtain a "Fire Intensity (FI) ", as the output corresponding to the fuzzy decision determined by Fuzzification and Defuzzification.The process is further repeated until the CO_2 level falls below the 1000ppm threshold, at which point the loop is terminated.

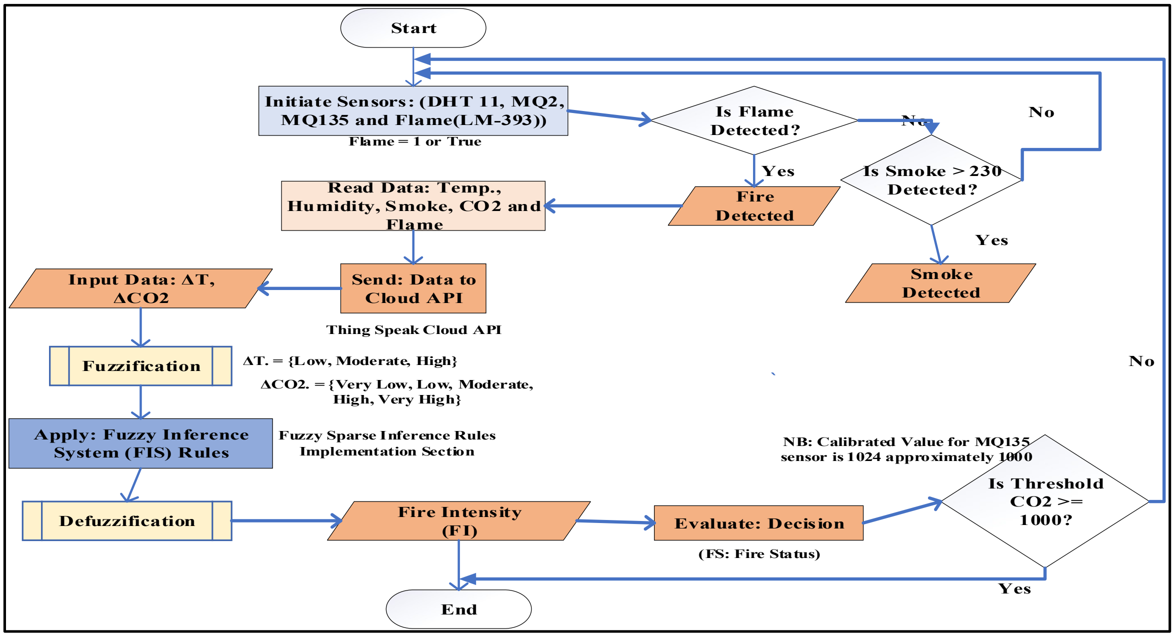


Fig. 5.5: Workflow Diagram of the Proposed Fire Detection Systems Prototype Framework Using Fuzzy Application Methods.

5.6.3 Hardware Components Used, Detailed Features and Specifications.

Hardware Component	Features and Specifications	Description
MQ135 Gas Sensor.	- Current Operating Voltage +5V± 0.1 AC or DC - Detecting Range 10-1000ppm - Load Resistance (RL), Adjustable - Target Gases: Hydrogen, Benzene, Sulphide, Smoke, CO_2 and Ammonia - Fast Response and High Sensitivity - Analog output of 0-5V - Digital Output of 0 or 5V (TTL Logic) - Pre-heat duration of 20 seconds. - Can be used as a digital or analogue sensor. For detailed information refer to datasheet @: https://components101.com/sites/default/files/component_datasheet/MQ135%20Datasheet.pdf	The Gas Sensor, is used for detecting presence of CO_2 (ppm) in the Proposed Prototype Experiment.
MQ2 Smoke Sensor.	- Uses an Operating Voltage +5V, - With an approximate heating consumption of <800mW - Detecting Range Concentrations of 200ppm -10000ppm - Target Gases: LPG, Smoke, Alcohol, Hydrogen, Propane, Methane and Carbon Monoxide. - Load Resistance 20KΩ - Sensing Resistance 10-60 KΩ For detailed information refer to datasheet @: https://components101.com/sites/default/files/component_datasheet/MQ2%20Gas%20sensor.pdf	Used for Detecting the Presence of any Smoke Levels (ppm) as per the Experimental Study.

DHT 11	• Operating Voltage 3.5 – 5V • Operating Current 0.3mA • Temperature Range 0-50 ^{0}C • Humidity Range 20-90% Resolution • Temperature and Humidity both with a 16-bit accuracy: ±1 ^{0}C and ±1% For detailed information refer to datasheet @: https://components101.com/sites/default/files/component_datasheet/DHT11-Temperature-Sensor.pdf	For reading the Temperature and Relative Humidity of the surrounding environment.
ESP8266 Wi-Fi Module	• Low cost, compact and powerful Wi-Fi Module • Power Supply: +3.3V only • Uses a Current Consumption of 100mA • I/O Voltage: 3.6V (max) • Input/Output (I/O) source current: 12mA (max) • Built-in low power of 32-bit MCU @ 80MHz • 512kB Flash Memory • Can be used as Station or Access Point or both combined • Supports Deep sleep (<10uA) • Supports serial communication hence compatible with many developments' platform like Arduino • Can be programmed using Arduino IDE or AT-commands or Lua Script • For detailed information refer to datasheet @: • https://components101.com/sites/default/files/component_datasheet/ESP8266%20Datasheet.pdf	This component is mainly used in providing internet connectivity to the developed project
Active Piezo Buzzer	• Rated Voltage: 6V DC • Operating Voltage: 4-8V DC • Rated current: <30mA • Sound Type: Continuous Beep • Resonant Frequency: ~2300 Hz • Small and neat sealed package • Breadboard and Perf board friendly • For detailed information refer to datasheet @: https://components101.com/sites/default/files/component_datasheet/Buzzer%20Datasheet.pdf	Used for Providing a signalling sound through the alarm notification mechanism once a potential fire is detected.
Breadboard	• 2 Distribution Strips, 200 tie-points • 630 tie-points in IC/ circuit areas • ABS plastic with colour legend • Dimension: 6.5*4.4*0.3 inch • Hole/Pitch Style: Square wire holes (2.54mm) • ABS heat Distortion Temperature: 84° C (183° F) • Rating: 300/3 to 5Amps • Insulation Resistance: 500MΩ / DC500V • Withstanding Voltage: 1,000V AC / 1 minute • Insertion Wire Size: 21 to 26 AWG wire • For detailed information refer to datasheet @: https://components101.com/sites/default/files/component_datasheet/Breadboard%20Datasheet.pdf	Prototyping and testing our fire detection systems design through Integrating all sensor components or modules in the Experiment.

Light Emitting Diode (LED)	• Superior weather resistance • 5mm Round Standard Directivity • UV Resistant Eproxy • Forward Current (IF): 30mA • Forward Voltage (VF): 1.8V to 2.4V • Reverse Voltage: 5V • Operating Temperature: -30℃ to +85℃ • Storage Temperature: -40℃ to +100℃ • Luminous Intensity: 20mcd • For detailed information refer to the datasheet @ https://components101.com/sites/default/files/component_datasheet/5mm-LED-Datasheet.pdf	Offers signal notification inform of light for any fire accidents detected.

Table 5.4: Detailed Worksheet Specifications and Features of all Hardware Components Used in the Implementation of the Fire Detection Systems Prototype

5.6.4 Lab. Setup Experiment of Proposed Fire Detection System Prototype

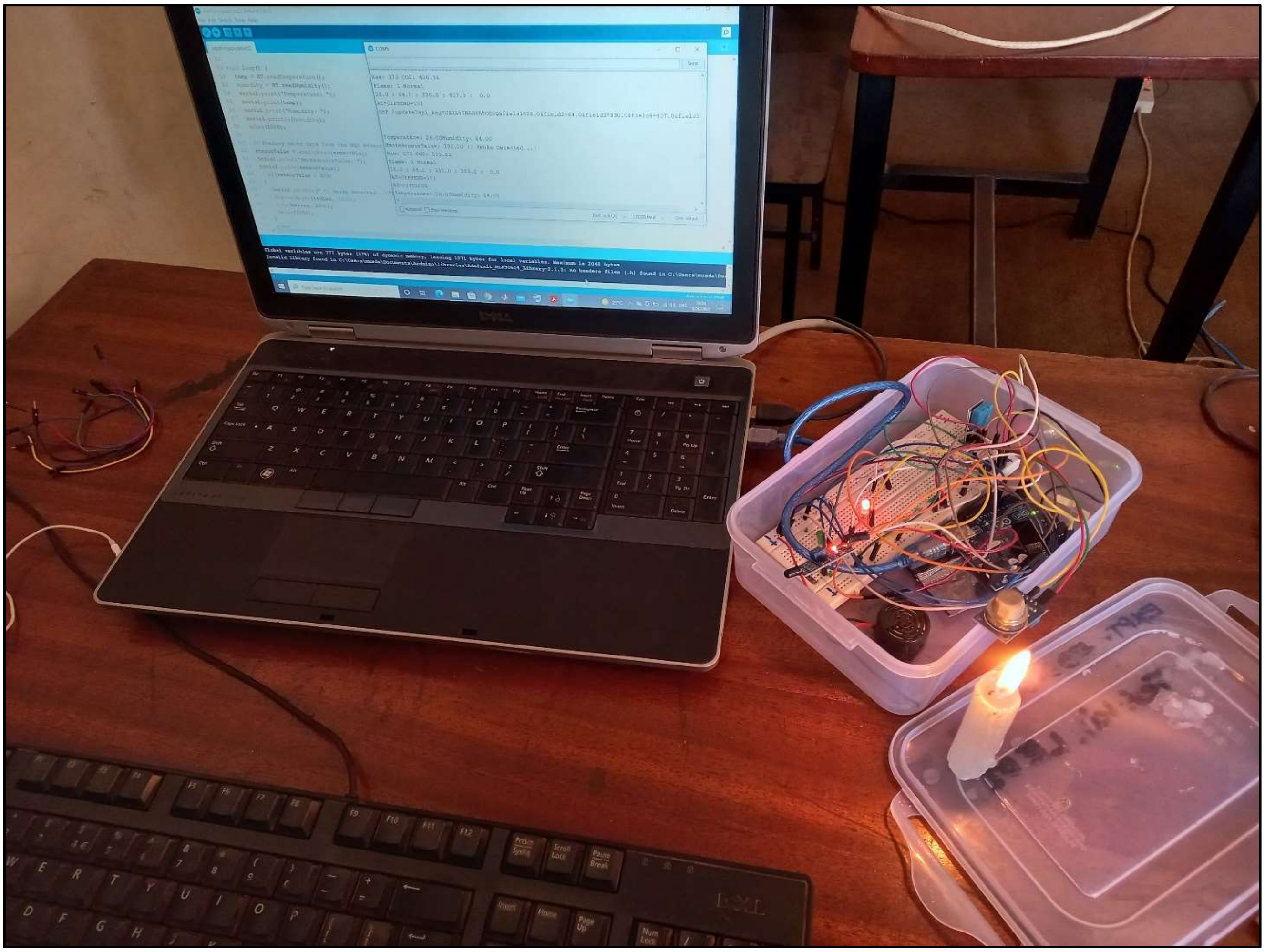
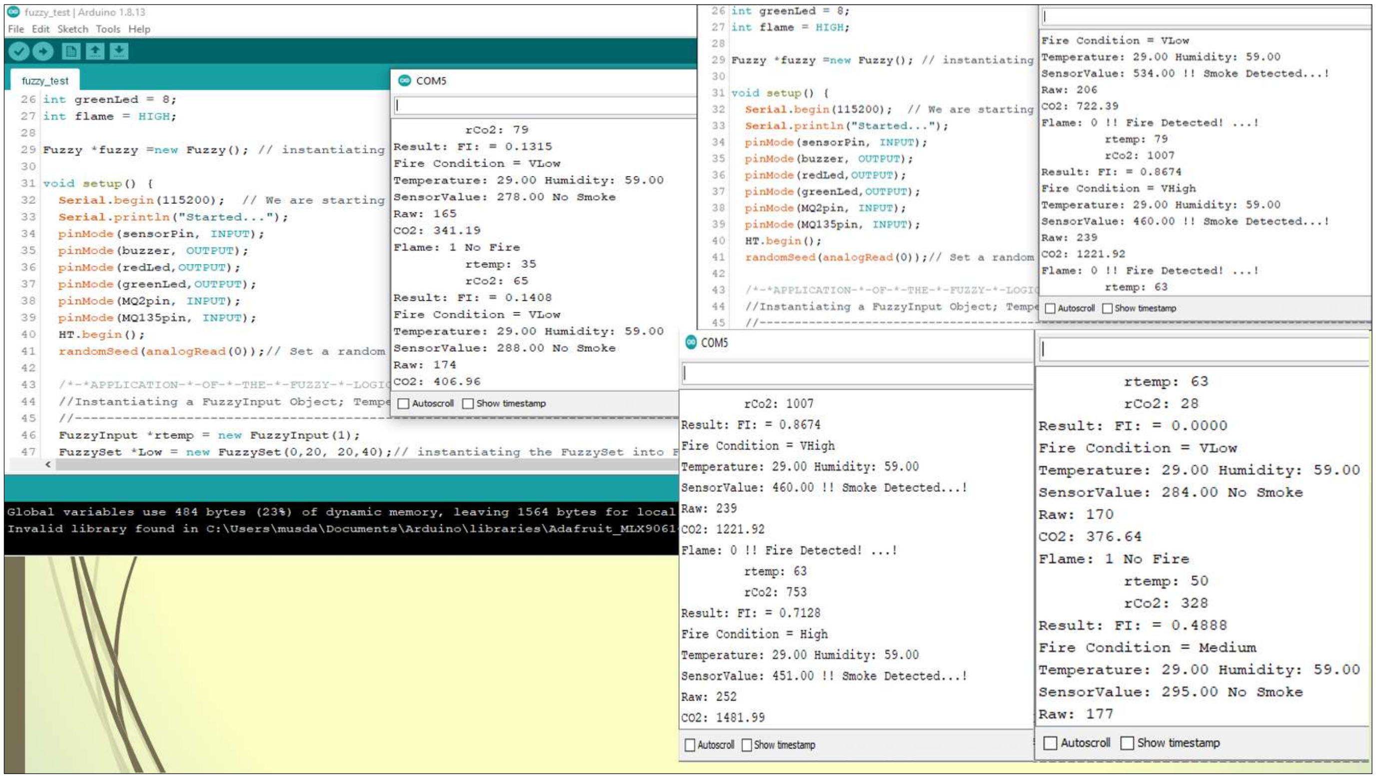


Fig. 5.6: Lab. Setup Experiment of the Proposed Low-Cost Fire Detection Systems Prototype Using Fuzzy Application Methods.

5.6.5 Results and Discussion



```
int greenLed = 8;
int flame = HIGH;

Fuzzy *fuzzy =new Fuzzy(); // instantiating

void setup() {
  Serial.begin(115200);  // We are starting
  Serial.println("Started...");
  pinMode(sensorPin, INPUT);
  pinMode(buzzer, OUTPUT);
  pinMode(redLed,OUTPUT);
  pinMode(greenLed,OUTPUT);
  pinMode(MQ2pin, INPUT);
  pinMode(MQ135pin, INPUT);
  HT.begin();
  randomSeed(analogRead(0));// Set a random

  /*-*APPLICATION-*-OF-*-THE-*-FUZZY-*-LOGIC
  //Instantiating a FuzzyInput Object; Tempe
  //-------------------------------------
  FuzzyInput *rtemp = new FuzzyInput(1);
  FuzzySet *Low = new FuzzySet(0,20, 20,40);// instantiating the FuzzySet into F
```

```
Global variables use 484 bytes (23%) of dynamic memory, leaving 1564 bytes for local
Invalid library found in C:\Users\musda\Documents\Arduino\libraries\Adafruit_MLX9061
```

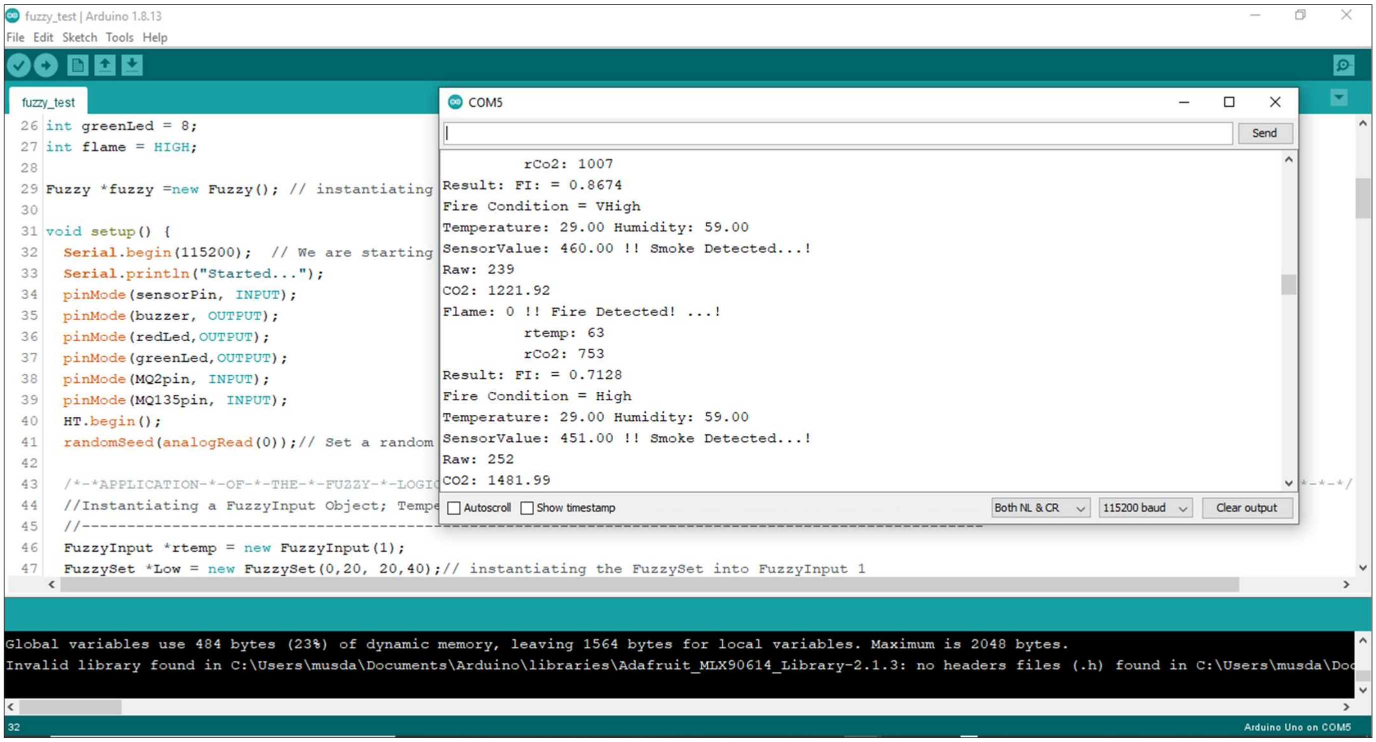
```
        rCo2: 79
Result: FI: = 0.1315
Fire Condition = VLow
Temperature: 29.00 Humidity: 59.00
SensorValue: 278.00 No Smoke
Raw: 165
CO2: 341.19
Flame: 1 No Fire
        rtemp: 35
        rCo2: 65
Result: FI: = 0.1408
Fire Condition = VLow
Temperature: 29.00 Humidity: 59.00
SensorValue: 288.00 No Smoke
Raw: 174
CO2: 406.96
```

```
Fire Condition = VLow
Temperature: 29.00 Humidity: 59.00
SensorValue: 534.00 !! Smoke Detected...!
Raw: 206
CO2: 722.39
Flame: 0 !! Fire Detected! ...!
        rtemp: 79
        rCo2: 1007
Result: FI: = 0.8674
Fire Condition = VHigh
Temperature: 29.00 Humidity: 59.00
SensorValue: 460.00 !! Smoke Detected...!
Raw: 239
CO2: 1221.92
Flame: 0 !! Fire Detected! ...!
        rtemp: 63
```

```
        rCo2: 1007
Result: FI: = 0.8674
Fire Condition = VHigh
Temperature: 29.00 Humidity: 59.00
SensorValue: 460.00 !! Smoke Detected...!
Raw: 239
CO2: 1221.92
Flame: 0 !! Fire Detected! ...!
        rtemp: 63
        rCo2: 753
Result: FI: = 0.7128
Fire Condition = High
Temperature: 29.00 Humidity: 59.00
SensorValue: 451.00 !! Smoke Detected...!
Raw: 252
CO2: 1481.99
```

```
        rtemp: 63
        rCo2: 28
Result: FI: = 0.0000
Fire Condition = VLow
Temperature: 29.00 Humidity: 59.00
SensorValue: 284.00 No Smoke
Raw: 170
CO2: 376.64
Flame: 1 No Fire
        rtemp: 50
        rCo2: 328
Result: FI: = 0.4888
Fire Condition = Medium
Temperature: 29.00 Humidity: 59.00
SensorValue: 295.00 No Smoke
Raw: 177
```

(a)

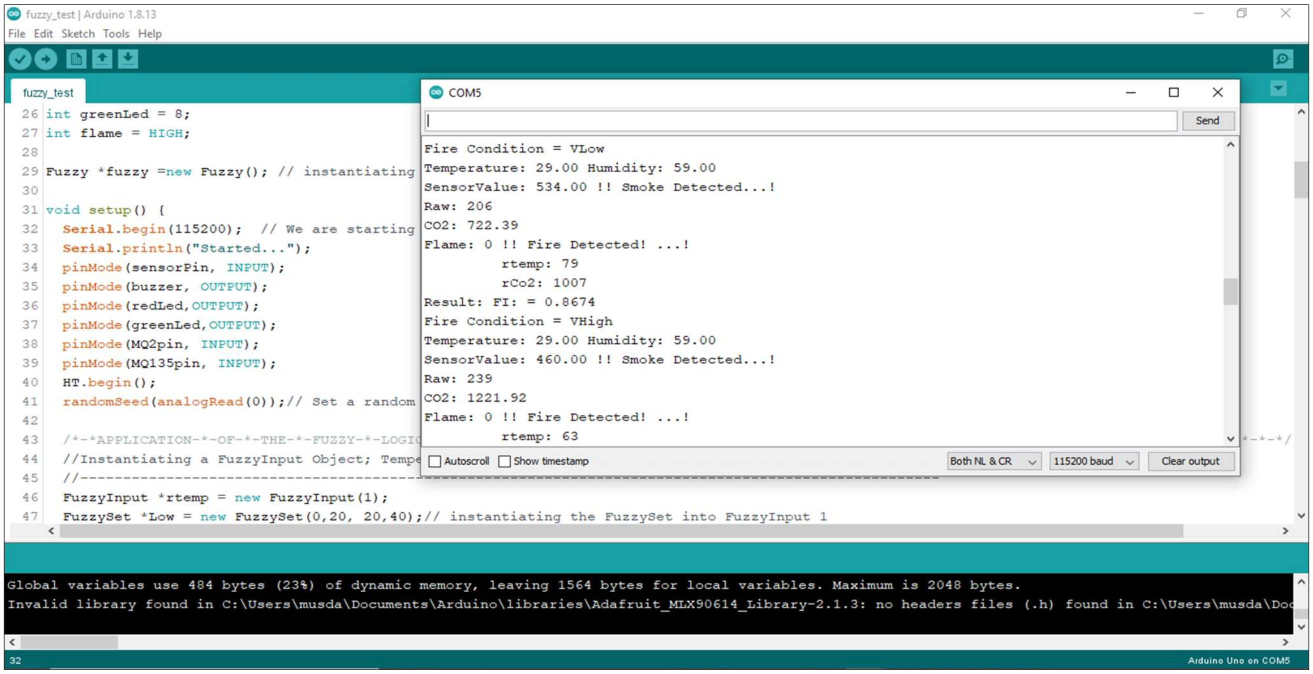


```
int greenLed = 8;
int flame = HIGH;

Fuzzy *fuzzy =new Fuzzy(); // instantiating

void setup() {
  Serial.begin(115200);  // We are starting
  Serial.println("Started...");
  pinMode(sensorPin, INPUT);
  pinMode(buzzer, OUTPUT);
  pinMode(redLed,OUTPUT);
  pinMode(greenLed,OUTPUT);
  pinMode(MQ2pin, INPUT);
  pinMode(MQ135pin, INPUT);
  HT.begin();
  randomSeed(analogRead(0));// Set a random

  /*-*APPLICATION-*-OF-*-THE-*-FUZZY-*-LOGIC
  //Instantiating a FuzzyInput Object; Tempe
  //-------------------------------------
  FuzzyInput *rtemp = new FuzzyInput(1);
  FuzzySet *Low = new FuzzySet(0,20, 20,40);// instantiating the FuzzySet into FuzzyInput 1
```

```
        rCo2: 1007
Result: FI: = 0.8674
Fire Condition = VHigh
Temperature: 29.00 Humidity: 59.00
SensorValue: 460.00 !! Smoke Detected...!
Raw: 239
CO2: 1221.92
Flame: 0 !! Fire Detected! ...!
        rtemp: 63
        rCo2: 753
Result: FI: = 0.7128
Fire Condition = High
Temperature: 29.00 Humidity: 59.00
SensorValue: 451.00 !! Smoke Detected...!
Raw: 252
CO2: 1481.99
```

```
Global variables use 484 bytes (23%) of dynamic memory, leaving 1564 bytes for local variables. Maximum is 2048 bytes.
Invalid library found in C:\Users\musda\Documents\Arduino\libraries\Adafruit_MLX90614_Library-2.1.3: no headers files (.h) found in C:\Users\musda\Do
```

(b)



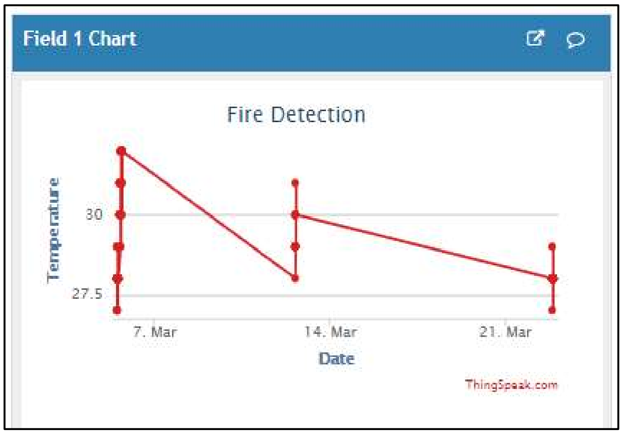
```
int greenLed = 8;
int flame = HIGH;

Fuzzy *fuzzy =new Fuzzy(); // instantiating

void setup() {
  Serial.begin(115200);  // We are starting
  Serial.println("Started...");
  pinMode(sensorPin, INPUT);
  pinMode(buzzer, OUTPUT);
  pinMode(redLed,OUTPUT);
  pinMode(greenLed,OUTPUT);
  pinMode(MQ2pin, INPUT);
  pinMode(MQ135pin, INPUT);
  HT.begin();
  randomSeed(analogRead(0));// Set a random

  /*-*APPLICATION-*-OF-*-THE-*-FUZZY-*-LOGIC                                  *-*-*/
  //Instantiating a FuzzyInput Object; Tempe
  //------------------------------------------------------------------------------------------
  FuzzyInput *rtemp = new FuzzyInput(1);
  FuzzySet *Low = new FuzzySet(0,20, 20,40);// instantiating the FuzzySet into FuzzyInput 1
```

```
Fire Condition = VLow
Temperature: 29.00 Humidity: 59.00
SensorValue: 534.00 !! Smoke Detected...!
Raw: 206
CO2: 722.39
Flame: 0 !! Fire Detected! ...!
         rtemp: 79
         rCo2: 1007
Result: FI: = 0.8674
Fire Condition = VHigh
Temperature: 29.00 Humidity: 59.00
SensorValue: 460.00 !! Smoke Detected...!
Raw: 239
CO2: 1221.92
Flame: 0 !! Fire Detected! ...!
         rtemp: 63
```

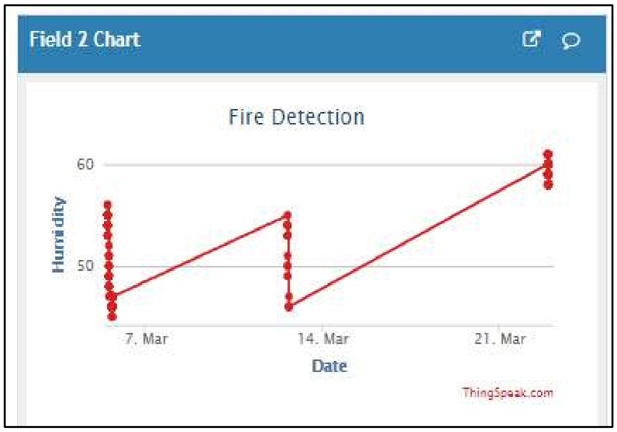
```
Global variables use 484 bytes (23%) of dynamic memory, leaving 1564 bytes for local variables. Maximum is 2048 bytes.
Invalid library found in C:\Users\musda\Documents\Arduino\libraries\Adafruit_MLX90614_Library-2.1.3: no headers files (.h) found in C:\Users\musda\Doc
```

(c)

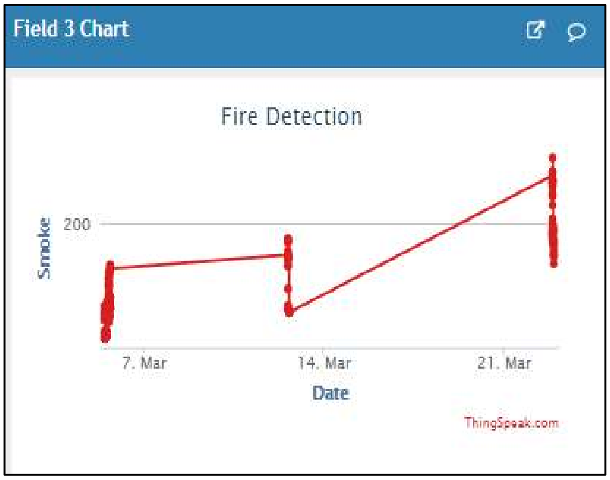
Fig. 5.7(a-c) Shows a Sampled Lab. Experiment. Snapshot of the Serial Monitor Output Results for the Proposed Fire Detection System Prototype.



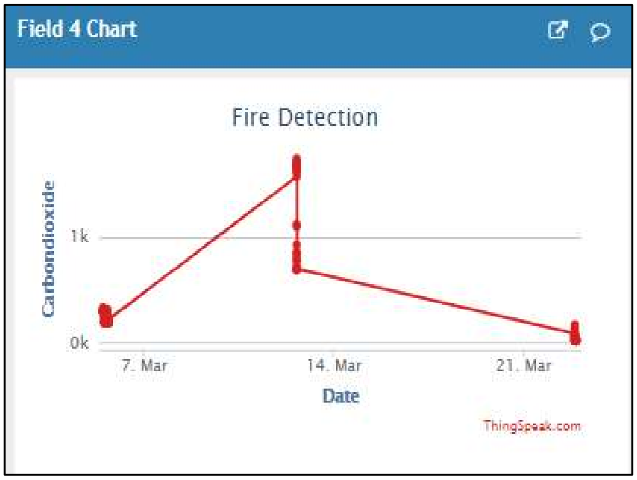
(a) Temperature Variation with Day/Time



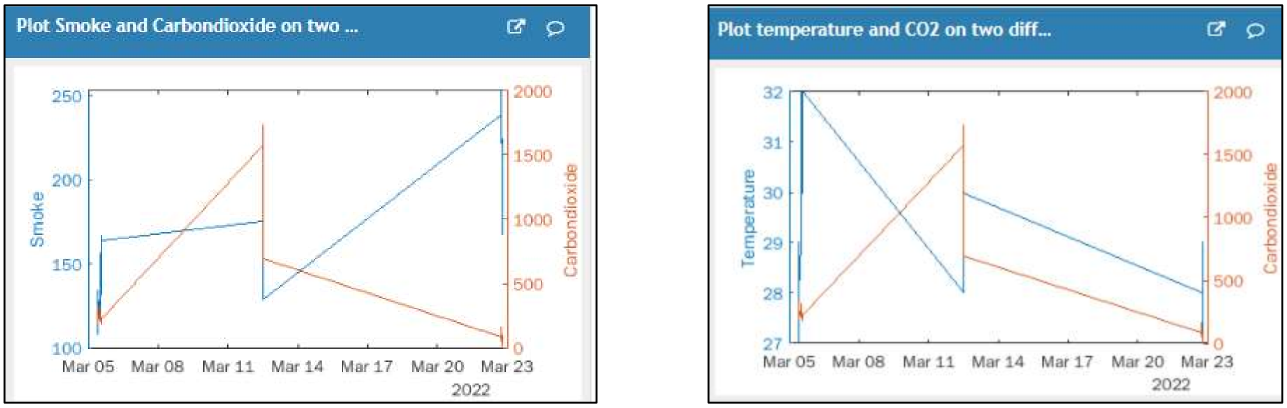
(b) Humidity Variation with Day/Time



(d) Smoke Variation with Day/Time



(e) Carbon dioxide Variation with Day/Time



(f) Smoke Vs Carbon dioxide Using

(g) Temperature Vs Carbon dioxide

Fig. 5.8(a-g): Graphical Insights of all Parameters Using Thing Speak Cloud API Embedded with the MATLAB Visualization Tool

In Fig. 5.8(a–g), we show the graphic output results generated from the proposed experiment. For instance, Fig. 5.8a depicts the temperature variation with day and time, which gradually rises once a "**fire is detected**" at temperatures above 30°C. Following this, the temperature returns to normal with "**no fire**" detected. Similarly, rising temperatures reduce atmospheric humidity significantly (cf. Fig. 5.8b). Fig. 5.8(f–g) shows the performance comparison of temperature, smoke, and CO_2 input parameters using the Thing speak cloud API in conjunction with the MATLAB 2018a visualization tool. Fig. 5.8f illustrates the correlation between smoke and CO_2 using a MATLAB tool. Results show that the concentration of smoke increases when smoke particles are detected in the atmosphere. As a result of increased levels of fire combustion, fire detection raises the level of CO_2 in the atmosphere above the 1000 ppm threshold. Also, Fig. 5.8f shows a gradual increase in smoke concentration, increased CO_2 levels due to high levels of O_2, and subsequent drops resulting in O_2 depletion. Likewise, Fig. 5.8g shows that higher temperatures require a gradual increase in the amount of CO_2 dissipated above the threshold value, followed by abrupt drops at lower temperatures.

Expt. No.	**Temp. (^{0}C)**	**Hum. (%)**	**Smoke (Conc).**	**Smoke Cond.**	**CO_2 (Conc).**	**CO_2 (ppm)**	**Flame Sensor**	**Fire Cond.**	**Fuzzy Temp.**	**Fuzzy CO_2**	**F1**	**FS**
1.	29	59	225	No Smoke	138	195.38	1	No Fire	72	59	0.0000	VLow
2.	29	59	227	No Smoke	141	204.55	1	No Fire	58	49	0.0000	VLow
3.	29	59	227	No Smoke	141	199.93	1	No Fire	66	545	0.4888	Medium
4.	29	59	228	No Smoke	142	209.25	1	No Fire	21	45	0.1367	VLow
5.	28	58	221	No Smoke	131	161.72	1	No Fire	59	277	0.0000	VLow
6.	29	59	220	No Smoke	132	165.68	1	No Fire	41	758	0.0000	VLow
7.	28	58	220	No Smoke	132	165.68	1	No Fire	76	460	0.0000	VLow
8.	29	59	227	No Smoke	143	214.02	1	No Fire	31	500	0.4888	Medium
9.	28	58	243	No Smoke	160	308.32	1	No Fire	59	565	0.4888	Medium
10.	28	58	228	No Smoke	140	199.93	1	No Fire	0	657	0.0000	VLow
11.	28	58	230	No Smoke	141	204.55	0	!!Fire Detected!!	15	1006	0.0000	VLow
12.	28	58	232	No Smoke	144	218.88	0	!!Fire Detected!!	65	701	0.6843	High

13.	28	58	232	No Smoke	143	214.02	0	!!Fire Detected!!	61	589	0.4888	Medium
14.	28	58	232	No Smoke	143	214.02	0	!!Fire Detected!!	67	936	0.8687	VHigh
15.	28	58	232	No Smoke	143	214.02	1	No Fire	10	203	0.1442	VLow
16.	28	58	257	No Smoke	140	199.93	1	No Fire	49	881	0.0000	VLow
17.	29	59	517	!!Smoke Detected!!	150	255.22	1	No Fire	23	745	0.0000	VLow
18.	28	58	420	!!Smoke Detected!!	160	321.17	1	No Fire	75	696	0.6843	High
19.	29	59	374	!!Smoke Detected!!	139	199.93	1	No Fire	42	358	0.4888	Medium
20.	29	59	358	!!Smoke Detected!!	149	239.14	0	!!Fire Detected!!	75	181	0.0000	VLow
21.	29	59	346	!!Smoke Detected!!	154	277.89	0	!!Fire Detected!!	41	550	0.4888	Medium
22.	29	59	349	!!Smoke Detected!!	155	283.79	0	No Fire	61	858	0.8669	VHigh

Table 5.5: Extracted Summary of Results from the Serial Monitor of the Proposed Fire Detection Systems Prototype Experiment

KEY: **VLow** = Very Low, **VHigh** = Very High, **FI** = Fire Index, **FS** = Fire Status, **ppm** = parts per million, Smoke **Cond**. = Smoke Condition, **CO_2 Conc**. = CO_2 Concentration, **Fuzzy Temp.** = Fuzzy Input for Temperature in range of [1-100], and **Fuzzy CO_2** = Fuzzy Input for CO2 in range of [1-1023]

5.7 Determination of Accuracy Rate of the Proposed Fire Detection Prototype Expt.

From the obtained results in Table 5.5 above, we compute the average accuracy rate of the proposed fire detection system prototype, by classifying the output decision "Fire Status" values, using the confusion matrix model (CMM)[95][45][34], we identify the True Positives (TP), False Positives (FP), False Negatives (FN), and True Negatives (TN) from the obtained dataset (Sample Size =22 inference rule outcomes) results (cf. Table 5.6). The CMM defines the summary of the prediction results from the fuzzy-based classification problem results. Hence, the experiment's accuracy rate is 91%. Therefore, a confusion matrix is used to visualize important predictive analytics such as specificity, accuracy, and precision. As a result, the required accuracy rate is calculated as follows:

$$\textbf{Accuracy Rate} = \frac{\textbf{TP+TN}}{\textbf{TP+TN+FP+FN}} \textbf{ x 100\%} \tag{5.9}$$

Sample Size **For N = 22**	**Observed Positive Values**	**Observed Negative Values**	**Total**
Predicted Positive Values	TP = 19	FP = 2	21
Predicted Negative Values	FN = 0	TN = 1	01

Table 5.6: Derived Summary of the Confusion Matrix Model (CMM) for the Proposed Fire Detection System Prototype.

5.8 Conclusion & Future Works

The study presents a novel idea of using Mamdani's' sparse-base fuzzy inference methods in the hardware design and implementation of a low-cost fire detection system prototype for local urban markets in Uganda or East Africa (EA), with the purpose of ensuring early fire protection and safety within the market community. The experimental results obtained for (Sample Size N = 22 inference rule outcomes) in Table 5.5 were evaluated using the confusion matrix model (CMM), which achieved an operating accuracy rate of 91%. Hence, the proposed solution assists the fire and rescue department and the local vendor community as a foundation in providing reliable early warning notifications by promoting appropriate public fire safety and protection measures and ensuring quick evacuation of affected persons. Future works intend to use machine learning (ML) or convolutional neural networks (CNN) techniques to design and implement effective low-cost fire detection systems or devices to significantly increase the rate of accuracy of the proposed solution prototype, thus minimizing the rate of false alerts.

CHAPTER 6

LIMITATIONS, RECOMMENDATIONS, SUMMARIZED THESIS CONTRIBUTIONS, CONCLUSIONS & FUTURE WORKS

6.1 Introduction

Local urban markets in Uganda must ensure proper fire safety planning principles. Hence, a set of working practices must be designed to reduce the severe destruction caused by fire outbreaks, also referred to as "fire safety"[96]. Therefore, for proper fire safety planning and management, four principles must be adhered to: life safety, notifications, extinguishment, and relocation or evacuation. As a result, local markets must implement the following control and mitigation measures or recommendations (ref. Sect. 6.2) to both the government and the market community in order to ensure proper improvement of fire disaster preparedness:

6.2 Summary of Challenges, Current Situation, Limitations, and Recommendations

S/No.	Challenges	Present or Current Situation	Shortcomings	Mitigation Measures or Proposed Recommendations
1.	Lack of Fire Detection Systems to Provide Early warning Notification with minimal Delays Due to Fire Outbreaks.	Fire detection systems haven't been installed in some commercial buildings, local markets to ensure safety evacuation due to fire disasters. Current Markets Administrators are quite ignorant of the importance of fire warning systems to the markets vendors and the nearby public community.	Leads to an extensive damage to both life and property, if no prior warning systems in place to notify the Fire & Rescue Services Dept. Lack of warning systems may lead to an increased cases of victims due to severe injuries or fatalities resulting into a fire accident.	Requirement to Install Smart IoT Based Fire Detection Systems for Early Warning Systems Minimizes Future Fire Disaster Damages and Extensive Damages. Acquired data can be used in future modeling & future predictions of fire behavioral patterns such that new techniques of fire suppression, measures can be applied through using Big Data Analytics or Data Science with appropriate Artificial Intelligence (AI) algorithms. Suggest procurement & Installation of appropriate fire protection and safety systems by law such as: smoke or fire alarms on every floor of the commercial buildings, markets to control to notify responsible authorities for immediate action. Gov't should pattern with telecommunication companies through the fire & rescue dept. of Uganda Police Force (UPF), to offer service free disaster warning messages in case of a fire outbreak using their available network infrastructure since it has a larger coverage area and the scene can be located using google map locations.
2.	Lack of Hydrants in some facilities forcing fire fighters to move to locations distant from the scene to get water.	Because of lack of the nearby fire hydrants. Fire fighter draw water from far distant locations from the scene of fire amidst	Hence, because of the delays in getting water from distant water supply points may lead to massive destructions by	For effective fire suppression and containment, fire hydrants should be adequately procured installed to the nearest distant source hence, reducing on the delays to a water source. This improves on the efficiency of firefighting department.

		heavy traffic jams on the roads.	fire due to delayed time of arrival to the scene of fire.	
3.	Poor Infrastructural planning making it difficult to access routes for the firefighting team to reach the base fires	Most buildings premises within Kampala central and nearby urban areas are poorly planned or heavily congested without proper access routes for putting out the fires.	Inaccessible premises or routes may lead to huge disastrous consequences and extensive property damage related to fire outbreaks. Poor and substandard electrical installations in commercial buildings, markets and other public gazette places may cause unnecessary fires accidents due to electrical short circuits.	Ensure Frequent Building Inspection and Fire Safety Laws should be adhered to before tenant occupancy. Planning Authorities, Fire Alarms, Evacuation Systems Use electricity safely by training people on safe electricity usage to avoid unnecessary electrical short circuits. Ensure standardized quality electrical equipment, proper electrical installations and regular inspections of electrical wiring in buildings. Ensure Occupational Health and Safety Administration (OHSA) for workplace's Safety Health and Laws i.e., Fire Regulations & Fire Safety Protection. This protects occupants and minimizes damage associated with the fire. Ensure reliable and certified engineering architectural plans approved to cater for future fire disaster & safety evacuation systems. Ensure that Safety Laws & Regulations for all public commercial buildings have proper evacuation safety systems installed in event of a fire related accidents. For Uganda: The Uganda Institute of Professional Engineers (UIPE) should propose relevant Acts of Law, to curb unqualified and incompetent electrical engineers, who do not satisfy & follow safety engineering code of ethics for civil works, electrical and mechanical installations for public commercial buildings. Probably these engineers should be certified by the body weep out unprofessional engineers and culprits should be punished, stripping their electrical license for poor installations.
4.	Lack of Comprehensive Fire Safety Laws or Fire Safety Bills to Compel Institutions, Schools, Markets & Public Premises to Implement Fire Safety Regulations.	Fire Safety Laws or Proposed Bills or Acts of Parliament are N/A. No adherence to fire safety laws & standards for proper planning fire outbreaks assurances & guidelines for appropriate	Lack of appropriate Laws, or Bills discourages fire safety standardization procedures for commercial building, local markets or public gazette places to ensure proper fire safety	Promote and aggressively encourage civic education through appropriate sensitization and fire safety awareness campaigns to the Public, Community, Building Owners and other relevant stakeholders of the fire laws, safety guidelines & regulations, proper use of electrical appliances in domestic homes and recommend proper mitigation measures for any fire related situations in order to minimize extensive damages to life and property.

		electrical installations in public commercial premises and trade business centers. As per the 2020 UPF report, fire safety protection and enhancements services have been introduced.	guideline and procedures are followed by all stakeholders, say the market vendors, and or nearby community.	Conduct professional trainings of trainers of fire safety professionals in fire safety protection, and fire risk assessments management who should be certified fire marshals or firefighters. Defaulters of commercial building owners should be fined for not adhering to fire and safety protection laws and regulations with immediate closure if enacted laws are not rightfully respected. Encourage Active Participation of the Trainings in the local people or community as part of capacity building in firefighting skills and report immediately any sight of an impendent fire accident. Encourage and Promote the Issuance of Incentives such as: Fire Safety Certification should be awarded to the Trainees in firefighting skills. Propose the Enactment & Enforcement of Fire risk Bans & Restriction Laws for Ensuring Safety and Protection of the of the Public Community or Premises. The major purpose of legislation is to support & institutionalize the fire risk management practices and protection services between the government and relevant stakeholders. Institute the Occupation Health and Safety Acts (OHSA), 2006 Enacted to ensure sure proper fire safety protection & management for all properties or premises affected. Gov't should provide exclusive non tax incentive for fire protection & safety equipment in order to encourage property owners to strictly adherence to the fire disaster phenomenon and its related associated risks.
5.	Lack of fixed or automatic fire suppression systems such as fire sprinklers, hose reels and landing valves to control the fire spread as fire brigades are on the way to the scene.	Fixed Fire Suppression Systems N/A to control the initial spread of fire at the scene.	Fires become wild and uncontrollable as the fire brigade arrives at the scene of fire. Most commercial building lack fire suppression systems in place to control spreading fires.	Proper Procurement & Acquisition of Horse Reels, & Landing Gears in order to assist in the initial control of the spread of wild fires with the sole aim of minimizing extensive damages to property and human lives. Fire sprinkler systems should be installed in large commercial buildings by law to control fire spread in case of a fire accident. Building Inspectors should enforce fire protections laws for commercial building & ensure fixed fire suppression systems are also installed in several areas before its occupied.

6	Fabrication of the Proposed Fire Detection System Prototype was not achieved.	Lack of materials to support actual fabrication of product.	Inadequate board materials due to less project funding. Limited Time for PhD completion.	Fabrication of a Proposed Fire Detection Systems Prototype Solution for Commercial Production of a Finished Product for Sale.

Table 6.1: Detailed Summary of Challenges, Present Situation, Limitations, and Proposed Recommendations.

6.3 Summarized Thesis Contributions

6.3.1 Design of an IoT-Based Fuzzy Approximation Prediction Model for Early Fire Detection to Aid Public Safety and Control in the Local Urban Markets

Firstly, the study presents a novel idea of a fire detection model to aid in early fire detection through the provision of true alarm notification to the local urban market communities within EA. To test the overall performance of the proposed fire detection model, several environmental parameters were considered namely; temperature, humidity, CO_2, CO, and flame and simulated using MATLAB 2018a software. The obtained results show that an accuracy rate of 95.83% was achieved by the proposed model. Hence, the proposed approach allows for future public safety monitoring and management of fire-related problems in the market community. Thus, fire safety monitoring is important in providing future fire safety planning, control, and management by enacting appropriate fire safety laws, policies, legislation, and associated fire safety practices or guidelines to be used in public buildings, market centers, and other public gazette locations.

6.3.2 Interval Type-2 Fuzzy Model for Intelligent Fire Intensity Detection Algorithm with Decision Making in Low-Power Devices

This study presents an intelligent interval type-2 TSK fire detection algorithm for decision-making in low-cost devices. Using a sparse rules approach and two resultant crisp input parameters, namely, A free open-source MATLAB 2018a/Simulink fuzzy toolbox is used to study the performance behavior of the IT2 TSK model. Results deduced that the output model accuracy significantly improved to 98.2%, MAE =1.3010, MSE = 1.6938, and RMSE = 1.3015 using regression analysis. Firefighters can properly comprehend the degree of fire threat by using the study. Therefore, the technique can be used in inexpensive fire detection systems to monitor the fire's status more accurately and with fewer false alarms. Early warning alerts enable prompt person evacuation through well-informed decision-making in inexpensive fire detection devices, improving fire safety management, surveillance, and community protection.

6.3.3 Hardware Design and Implementation of a Low Cost IoT-Based Fire Detection System Prototype Using Fuzzy Application Methods

Finally, using the Arduino UNO and Arduino IDE platforms in conjunction with the fuzzy logic technique, the study's hardware-based solution for a low-cost fire detection system prototype was implemented to determine an informed decision about the fire status. Based on the confusion matrix model (CMM) evaluation approach, obtained results demonstrate that the suggested fuzzy logic fire detection system prototype achieved an accuracy of 91%. By offering early warning alarm notification in the event of a fire outbreak, the suggested approach guarantees the neighboring market community proper public fire safety protection.

6.4 Conclusions & Future Works

Fires happen by accident and can cause significant loss and damage to both property and human life if not properly and effectively controlled. Therefore, this study focused mainly on local urban markets within Uganda, primarily because they are greatly affected by recurring fire outbreaks but lack adequate fire control measures. Furthermore, current human observation methods cause excessive delays in alerting appropriate authorities, resulting in significant property damage and human fatalities. Thus, the study proposed a hardware solution for a low-cost IoT-enabled fire detection system using fuzzy logic to provide early warning notifications with better decision-making and minimal false alerts. Therefore, proper fire management techniques should be implemented to minimize the level of damage and save lives in the surrounding market communities. Future Works intends to promote the fabrication of the proposed fire detection prototype circuit for purposes of commercial production of the product. In addition to developing and promoting a comprehensive fire safety risk assessment model, fire safety management, planning, and control methods within the local urban markets by examining fire hazards and people at risk through evaluating, recording, planning, and reviewing the damage and costs incurred. As a result, appropriate fire risk assessment models, fire safety laws, policies, and standards must be enacted in order to develop effective fire management and control practices for informed decision-making.

APPENDIX I: SAMPLE INTERVIEW GUIDE.

*CASE STUDY: ST. BALIKUDEMBE MARKET, UGANDA

*DOCUMENTS: ANNUAL UGANDA POLICE FORCE (UPF) REPORTS (2012-2021)

A. CAUSES OF FIRE OUTBREAKS (2012-2021)

i. What are the major causes of fire outbreaks in urban markets located in specifically in Uganda?

ii. What makes electrical short circuits or neglected charcoal stoves among others as the main cause of fire outbreaks in urban markets located in Uganda?

iii. Of the fire causes mentioned above, which one is the primary cause attributed to most of fire outbreaks in Uganda? Specifically in the local urban markets, and why?

iv. What are the main causes of fire outbreaks in public commercial buildings, kiosks or shops besides urban markets centers?

v. What measures or mitigation remedies has the government or the fire and rescue services department proposed in order to combat future causes of these fire accidents?

B. PREMISES OR PROPERTIES AFFECTED?

i. Which kind of properties/premises are mainly or mostly affected by these fire outbreaks and why?

ii. Have you carried out any fire safety & protection professional trainings or Occupational Safety and Health Administration (OHSA) to the building owners or workers to ensure fire safety within commercial buildings?

iii. Are there any documents or records on file, or could you tell the total number of premises/properties affected over the years between the period of (2012-2020)?

C. VICTIMS INJURED OR FATALITIES (2012-2020)?

i. What is the main cause of injury or death due to a fire outbreak?

ii. How many victims were affected by the fire outbreaks between the periods of (2012-2020)?
   a) In terms of total number of **Injured** or **Death** (Fatal) by fire outbreaks?
   b) Do you have any records or reports quoting the number of victims injured or died due to fire accidents over the years?

iii. How many or can you define the number of emergency fire incidences responded to by the fire & rescue department between the period of (2012-2020)?

iv. Do you have any records or documentation established on the causes, victims affected in all the years as a fire and rescue department?

v. How many emergencies rescue mission have you conducted between (2012-2020), and what number has been rescued, persons, animals etc. against fire incidences?

D. DISTRICTS OR DIVISIONS GREATLY AFFECTED BY FIRE OUTBREAKS?

Which districts or divisions or regions within Uganda have been greatly affected by the fire outbreaks and why?

E. CHALLENGES?

i. What are the major challenges faced by the fire and rescue services department in suppressing these fire outbreaks?
ii. What measures or procedures has the fire and rescue department proposed to counter the above-mentioned challenges?

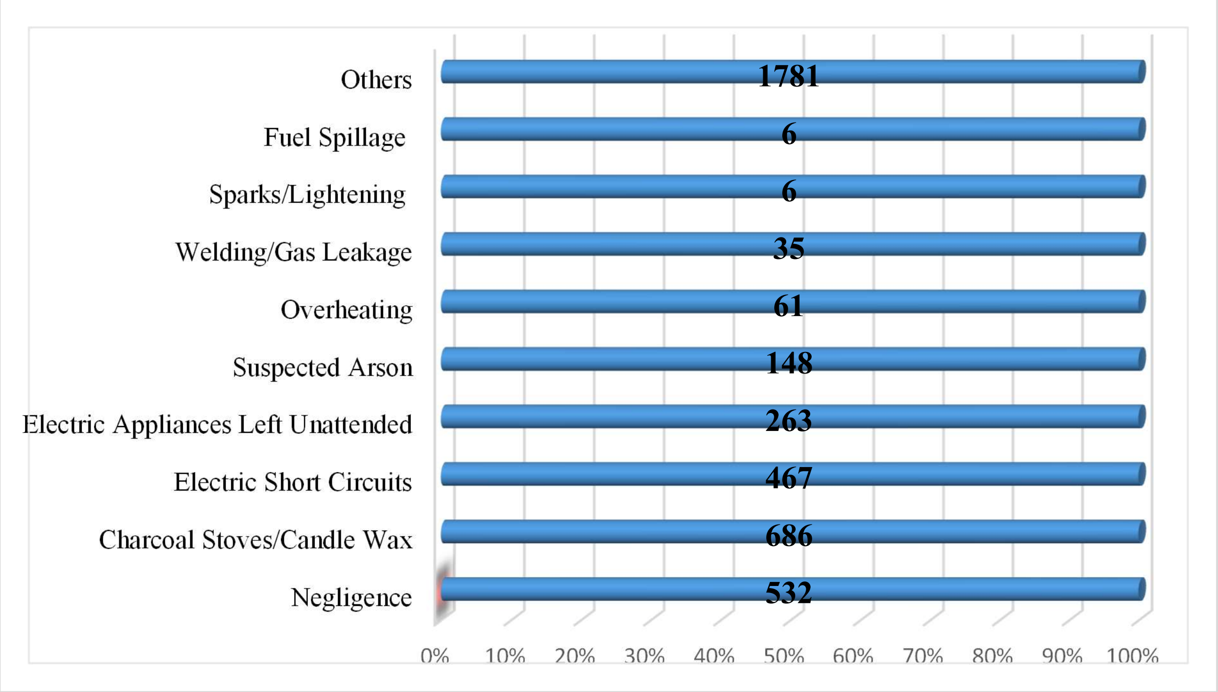
F. RECOMMENDATIONS?

i. Has the fire & rescue services department proposed any fire safety protection laws or legislations in place to control the spread of the fires and ensure safety of fire in commercial buildings, markets etc.?
ii. Have you carried any sensitization plans or some kind of awareness to the public community about the most common causes of fire and appropriate measures to avoid or protect the public against these fires?
iii. Are there any measures proposed in place by the government or the fire department in combating these fires?
iv. Have you proposed any measures or mitigations in place for poorly planned infrastructures or commercial buildings for proper fire management, Building Inspections, Laws and Fire Standardization Procedures for Commercial Buildings?
v. What measure have you put in place for training of trainers in fire management, Fire Inspectors, Fire Marshalls to effectively provide fire safety within the community?

APPENDIX II: Analysis of Collected Data:

Causes of Fire	**2017**	**2018**	**2019**	**2020**	**Total**
Negligence	109	186	187	50	**532**
Charcoal Stoves/Candle Wax	174	169	170	173	**686**
Electric Short Circuits	121	92	91	163	**467**
Electric Appliances Left Unattended	60	84	87	32	**263**
Suspected Arson	62	19	18	49	**148**
Overheating	22	4	4	31	**61**
Welding/Gas Leakage	29	3	3	-	**35**
Sparks/Lightening	-	2	1	3	**6**
Fuel Spillage	-	-	-	6	**6**
Others	468	458	434	421	**1781**

App. II: Table 7.1: Shows the primary causes of fire incidences in Uganda that were recorded between the period of (2017-2020)



App. II: Fig. 7.1: Shows the total number of the primary causes of fire outbreaks in Uganda that occurred between the years of (2017-2020).

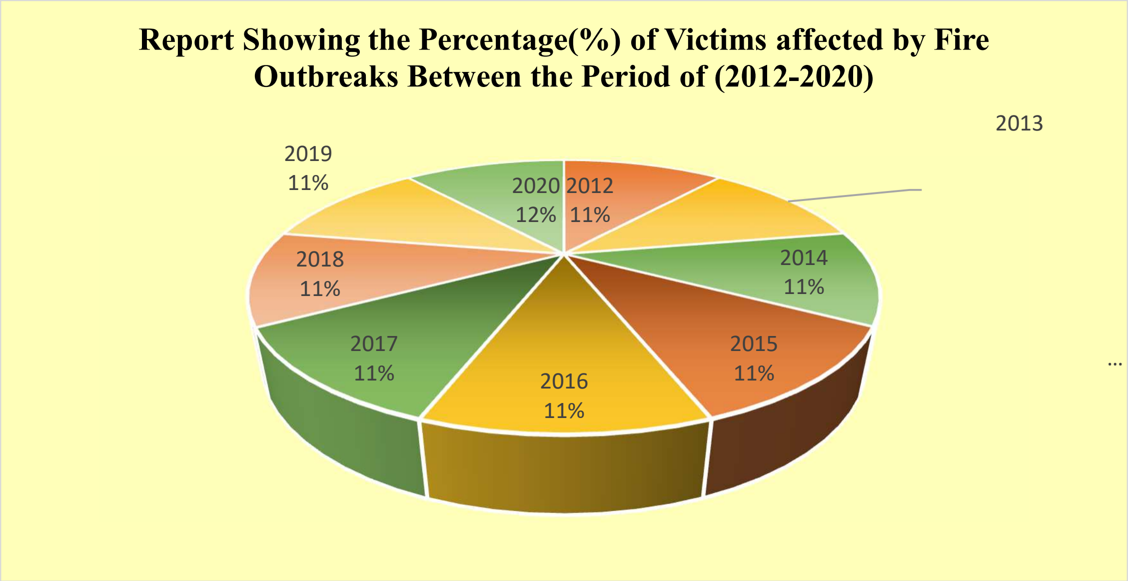
Source: Uganda Police Force Annual Crime Reports of (2017-2020); Department of Fire & Rescue Services, Uganda Police Force (UPF).

Premises Affected	**2012**	**2013**	**2014**	**2015**	**2018**	**2019**	**2020**	**Total**
Markets/Super Markets	7	20	5	26	1	16	1	**76**
Schools or Institutions, Residential Hostels or Dormitories	26	24	23	34	2	10	29	**148**
Commercial Buildings, Shops, Kiosks	263	140	77	247	163	163	169	**1222**
Residential Buildings or Homes	459	296	234	438	312	314	290	**2343**
Factories, Workshops, Warehouses, Stores	25	54	63	66	7	14	68	**297**
Farms, Forests, Plantations, Bush Burning & Open Grounds	42	46	16	87	12	24	26	**253**
Fuel Stations, Tankers	8	1	-	4	5	4	5	**27**
Automobiles, Garages	13	52	41	89	6	6	89	**296**
Poor Electrical Installations	81	89	111	148	117	117	100	**763**
Hospitals	-	4	1	20	-	-	-	**25**
Office Premises	-	6	-	41	-	-	-	**47**
Recreation Centers, Bars, Restaurants.	-	31	37	81	19	19	22	**209**
Miscellaneous/Unknown Cause	100	7	150	219	371	327	197	**1371**

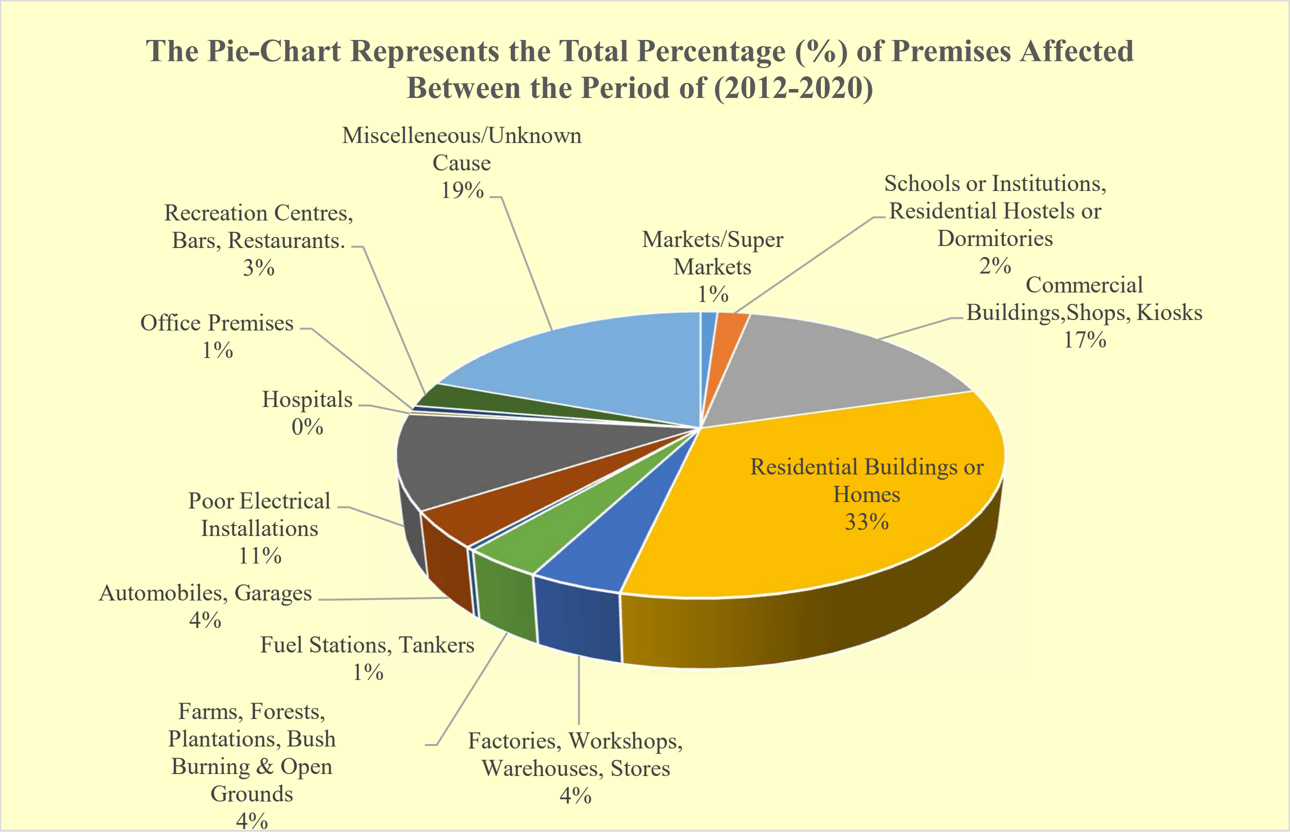
App. II: Table 7.2: Major properties/premises destroyed by fire outbreak incidences in Uganda between the period of (2012-2020)

S/No	**Nature**	**2012**	**2013**	**2014**	**2015**	**2016**	**2017**	**2018**	**2019**	**2020**
1	Injured	28	56	35	63	59	36	56	36	151
2	Fatal	22	62	54	38	32	23	32	46	77
	Total	**50**	**118**	**89**	**101**	**91**	**59**	**88**	**82**	**228**

App. II: Table 7.3: Shows the persons/victims affected by fire outbreaks in Uganda that were recorded between the period of (2012-2020)



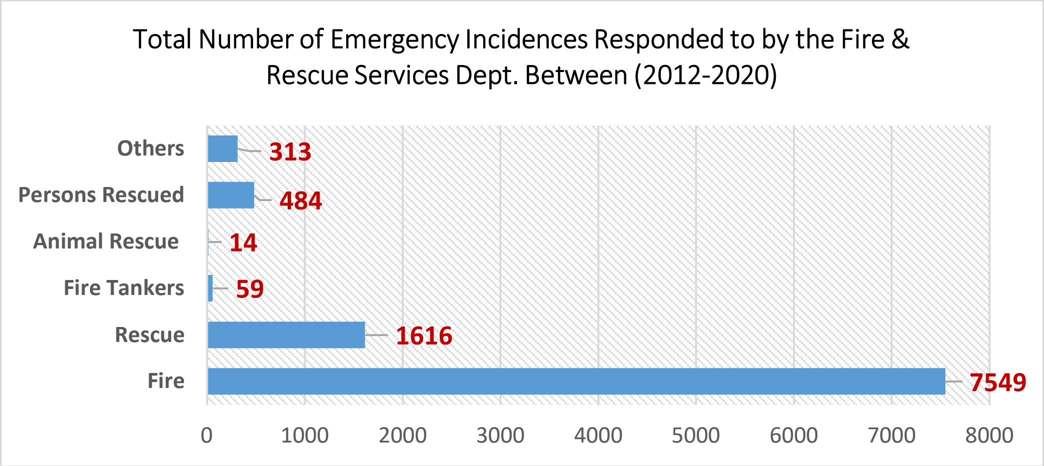
App. II: Fig. 7.2: Detailed Report Showing Percentage (%) of Victims Affected by Fire Outbreaks Between the Period of (2012-2020)



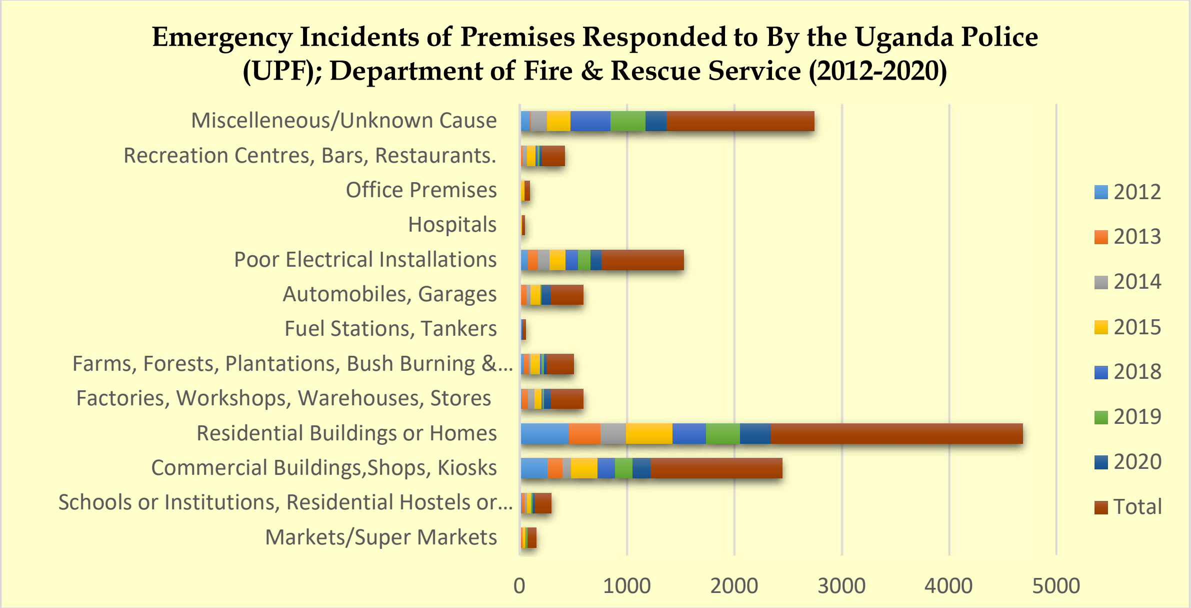
App. II: Fig.7.3: Percentage of Premises Affected by Fire Outbreaks Between the Period of (2012-2020)

Emergency Incidences Responded to by the UPF, Fire & Rescue Services Dept								
Emergency	**2012**	**2013**	**2016**	**2017**	**2018**	**2019**	**2020**	**Total**
Fire	1126	936	1356	1099	1018	999	1015	**7549**
Rescue	231	300	307	260	-	249	269	**1616**
Fire Tankers	15	44	-	-	-	-	-	**59**
Animal Rescue	-	14	-	-	-	-	-	**14**
Persons Rescued	-	-	180	107		46	151	**484**
Others	-	313	-	-	-	-	-	**313**

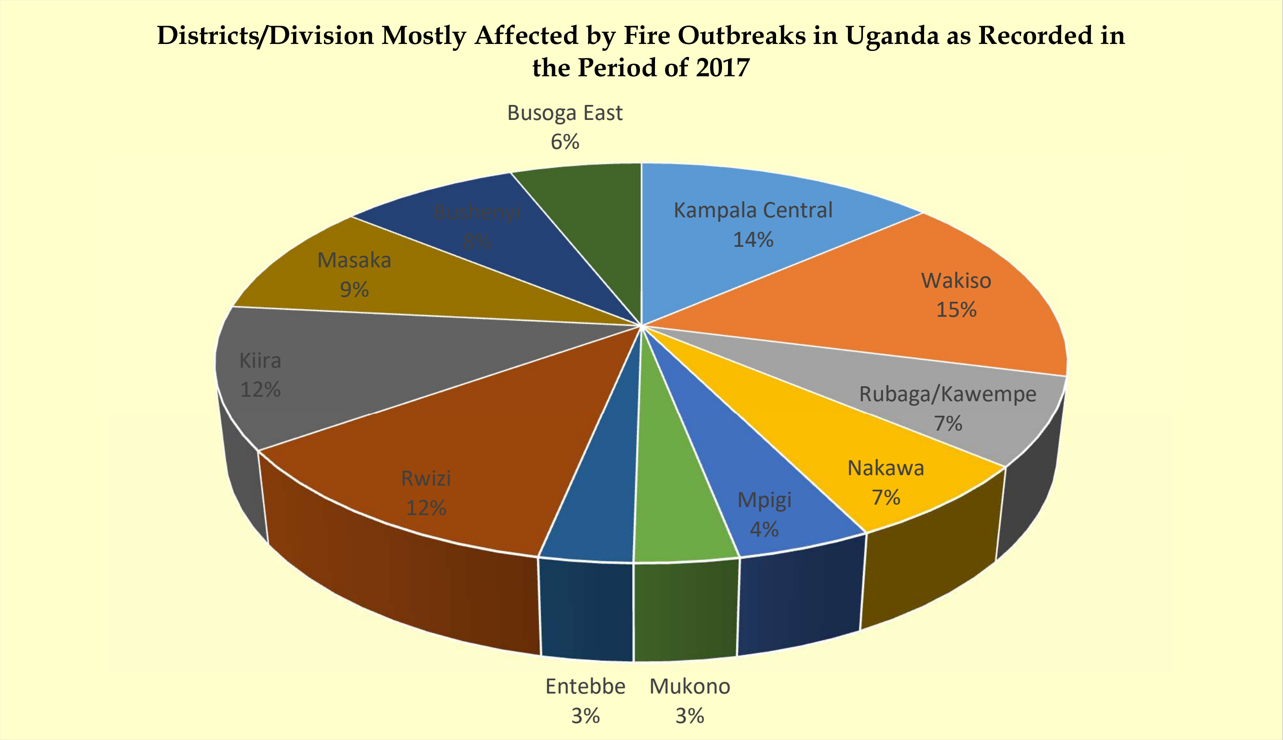
App. II: Table 7.4: Emergency Incidences Responded to By the Fire & Rescue Dept, of the Uganda Police Force (UPF) Between (2012-2020).



App. II: Fig. 7.4: Emergency Incidences Responded to By the Fire and Rescue Department, Uganda Police Force (UPF) (2012-2020)



App. II: Fig. 7.5: Emergency Premises Responded to By the Uganda Police Force (2012-2020)



App. II: Fig. 7.6: Shows Districts/Divisions Mostly Affected by Fire Accidents in Uganda Between the period of (2012-2020).

***Availability of Data and Materials**:

All Uganda Police Crime Annual Reports of (2012-2020) and available data about the fire outbreaks in Uganda can be accessed on: https://www.upf.go.ug/publications/

***Current Report: Uganda Police Annual Crime Reports (2021-2022)**

Section: Department of Fire and Rescue Services Report.
https://www.upf.go.ug/download/the-2022-annual-crime-report/
https://www.upf.go.ug/annual-crime-report-2021/

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***Academic Journal Publications:**

1. **E. Lule**, C. Mikeka, A. Ngenzi and D. Mukanyiligira, "Design of an IoT-Based Fuzzy Approximation Prediction Model for Early Fire Detection to Aid Public Safety and Control in the Local Urban Markets", *Symmetry,* Vol. 12, no. 9, p. 1391, 2020

2. **E. Lule**, C. Mikeka, A. Ngenzi and D. Mukanyiligira, "Interval type-2 fuzzy model for intelligent fire intensity detection algorithm with decision making in low-power devices," *Intelligent Automation & Soft Computing*, vol. 38, no.1, pp. 57–81, 2023.

3. **Lule, E**., Mikeka, C., Ngenzi, A., Mukanyiligira, D., Musdalifah, P. (2024). Hardware Design and Implementation of a Low-Cost IoT-Based Fire Detection System Prototype Using Fuzzy Application Methods. In: Silhavy, R., Silhavy, P. (eds) Data Analytics in System Engineering. CoMeSySo 2023. *Lecture Notes in Networks and Systems*, vol 910. Springer, Cham. https://doi.org/10.1007/978-3-031-53552-9_6