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ARTICLE

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

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ABSTRACT

Local markets in East Africa have been destroyed by raging fires, leading to the loss of life and property in the nearby communities. Electrical circuits, arson, and neglected charcoal stoves are the major causes of these fires. Previous methods, i.e., satellites, are expensive to maintain and cause unnecessary delays. Also, unit-smoke detectors are highly prone to false alerts. In this paper, an Interval Type-2 TSK fuzzy model for an intelligent lightweight fire intensity detection algorithm with decision-making in low-power devices is proposed using a sparse inference rules approach. A free open–source MATLAB/Simulink fuzzy toolbox integrated into MATLAB 2018a is used to investigate the performance of the Interval Type-2 fuzzy model. Two crisp input parameters, namely: $\widetilde{\mathbf{FI}}_{\mathbf{T}}$ and $\widetilde{\mathbf{FI}}_{\mathbf{G}}$ are used. Results show that the Interval Type-2 model achieved an accuracy value of $\widetilde{\mathbf{FI}}_{\mathbf{O}} = 98.2\%$, MAE = 1.3010, MSE = 1.6938 and RMSE = 1.3015 using regression analysis. The study shall assist the firefighting personnel in fully understanding and mitigating the current level of fire danger. As a result, the proposed solution can be fully implemented in low-cost, low-power fire detection systems to monitor the state of fire with improved accuracy and reduced false alerts. Through informed decision-making in low-cost fire detection devices, early warning notifications can be provided to aid in the rapid evacuation of people, thereby improving fire safety surveillance, management, and protection for the market community.

KEYWORDS

Interval type-2 (**IT2**) fuzzy systems; mean absolute error (**MAE**); mean square error (**MSE**); root mean square error (**RMSE**); tang sugeno kang (**TSK**); type-1 (**T1**) fuzzy systems

Abbreviations and Mathematical Symbols

Acronym	Description	Mathematical symbols/Description
$EFIP_1$ $EFIP_2$	Estimated Fire Intensity Prediction Due Temperature rise, Estimated Fire Intensity Prediction Due to Gases Dissipated, respectively	$\wedge$: Minimum Operator, $\vee$: Maximum Operators and, $\sqcup$: Joint Operation
IT2 TSK, T1, T2	Interval Type-2 Tang Sugeno Kang, Type-1 and Type-2 Fuzzy Logic Systems	$\overline{\boldsymbol{\alpha}}_i$: *T*he Firing Strength of the matching degree of similarity s and antecedent $\boldsymbol{x}_j$
MAE, MSE	Mean Absolute Error, and Mean Square Error	$\subseteq$: A subset of and, U: Initial Universe of Objects or a finite and non-empty set U
CO, CO_2	Carbon monoxide, Carbon dioxide	$\boldsymbol{\mu}$: Primary Degree of Membership
RMSE	Root Mean Square Error	J_x: Secondary Domain
TR	Type Reduction	F(ε): A Set of Approximate Elements of the Soft Set (F, A)
R^2	The Coefficient of Determination	μ: Type-2 Membership Function
MF, UMF, LMF	Member Function, Upper Membership Function, Lower Membership Function	X: The primary domain with input x

1 Introduction

Fire disasters are the most common occurrences in East Africa's densely populated local urban markets. For instance, Gisozi, Rwanda; Gikomba, Kenya; and Owino, Uganda, are constantly threatened by rampant fire accidents, which have caused severe loss of life and property (ref. Fig. 1). These markets, provide income for small-scale vendor communities by selling their daily wares. According to Uganda police investigative reports, the major causes of fires include; electrical short circuits, negligence, and neglected charcoal stoves [1–4]. The current vendor communities heavily rely on human patrol and observation methods. However, they are quite inefficient and may cause extensive damage to vendors' property due to unnecessary delays [2,3]. Also, unit–smoke detectors have a high rate of false alerts due to their high sensitivity calibration to their surrounding environment [5–7]. Ruchkin et al. [8–10] proposed satellite–based systems that are prohibitively expensive to acquire and maintain for developing countries. Camera systems are also incapable of monitoring the initial ignition of surface fires as well as the level of fire danger [11]. Related works are discussed in Table 1. This study therefore, presents an Interval Type-2 Tang Sugeno Kang fuzzy model for an intelligent fire intensity detection algorithm with decision making in low-power devices. The performance of the proposed model was investigated using a free open-source fuzzy toolbox integrated into MATLAB2018a. Two secondary input parameters, namely; fire intensity due temperature change ($\widetilde{FI_T}$) and fire intensity due to gases dissipated ($\widetilde{FI_G}$) are considered.

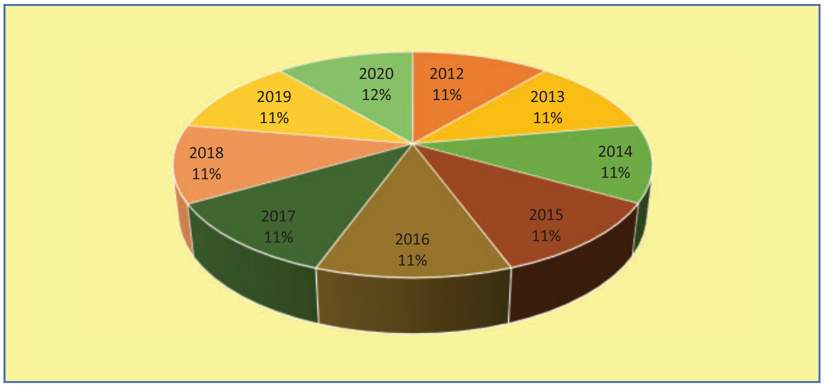


Figure 1: Percentage (%) of victims (injured, fatal) affected by fire accidents in the period (2012–2020), a case of Uganda [2]

Results show that the proposed Interval Type-2 TSK fuzzy model outperformed Mamdani's Type-1 by an accuracy of 98.2%, compared to 95.8% in Lule et al. [1]. The *footprint of uncertainty* (FOU) in the Interval Type-2 fuzzy sets provides additional degrees of freedom, allowing for the modelling of uncertainties to improve efficiency. Secondly, Type-2 systems outperformed Type-1 fuzzy systems in overcoming the dimensionality problem, which leads to the high computational overload associated with rule-based systems [12,13]. Thus, the model's efficiency significantly improved because the Interval Type-2 (IT2) TSK fuzzy model minimized the uncertainty errors inherent in Type-1 fuzzy systems [14].

Hence, a lightweight fire intensity detection algorithm based on the Interval Type-2 TSK fuzzy model for decision-making in low-power fire devices is presented. When compared to Mamdani's Type-1 systems, the Interval Type-2 TSK fuzzy method improved the model's accuracy to 98.2%, MAE = 1.3010, MSE = 1.6938, and RMSE = 1.3015 for effective fire detection. Thus, the proposed solution can be implemented in low-cost, low-power fire detection systems to improve the accuracy of monitoring the current state of fire. This shall assist the firefighting personnel in fully monitoring, understanding, and mitigating any level of the state of fire danger in order to make an appropriate decision. Early warning notifications can also be provided to aid in the rapid evaluation of persons, thereby improving fire safety surveillance, management, and protection for the market community through informed decision-making in low-cost fire devices. The remainder of the paper includes; Related Works, Materials and Methods, Second Order FAM, Algorithm Design Procedure, Relational Mathematical Operations Theory and Notations in Type-2 Fuzzy Systems, Simulation Experimental Setup, Results and Discussion, Conclusion, and Future Works.

2 Related Works

In the Table 1, we show a detailed discussion of the proposed solutions and their limitations for the related works.

Table 1: Summarized discussion of related works

Ref.	Proposed solution	Limitations
Sandra et al. [15]	Presents a low-cost LoRa network to assess the fire risks in rural areas. The system measures the temperature, humidity, wind speed, and CO_2 levels in the environment.	However, spectrum interference and LoRa payload data are limited for large datasets in the event of fire outbreaks.
Li et al. [16]	Proposed an image–based fire detection using convolution neural networks 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.
Surya Devi et al. [17]	Presented a fuzzy–based smart fire detection system. Uses DHT11, and MQ2 sensors to detect fire and sends a notification via WhatsApp and the web interface.	However, Type-1 systems are affected by inherent error uncertainties, whch decrease the performance of the desired outcome.
Sarwar et al. [18,19]	Presents an ANFIS to detect fire and provide a warning. The fire monitoring and warning application system is used for fire detection in smart buildings. Notification is sent via the GSM, and an accuracy of 95% was achieved.	The ANFIS yields better results than Type-1. However, the Interval Type-2 outperforms the ANFIS system technique significantly, yielding a better outcome.
Pacori et al. [20]	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.
Khule et al. [21], Park et al. [22]	A fire control system in vehicles is presented. Park presented a fire system to detect fire signatures using fuzzy logic, false alerts were reduced using parameters for flame, temperature, smoke, and CO_2.	However, Type-1 fuzzy systems are more prone to false alarm errors in vehicles compared to the proposed Type-2 fuzzy systems.
Listyorini et al. [23]	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.
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.

(Continued)

Table 1 (continued)

Ref.	Proposed solution	Limitations
Ikbar et al. [25]	Proposed a robot that uses a control method to detect fire. The flame, ultrasonic sensors, and Arduino Mega 2560 were used. Robotic movement controlled by fuzzy logic successfully detected fire on a candle placed 20 cm.	However, using Type-1 fuzzy control obtained less accurate results compared to the proposed Interval Type-2 TSK approach.

3 Materials and Methods

The study employs a free open-source MATLAB/Simulink fuzzy toolbox integrated with Interval Type-2 fuzzy logic system. Because it is widely available to the users of Type-2 fuzzy systems community. The simulink library connects the fuzzy logic system and the fuzzy toolbox. To study the performance of the IT2 TSK fuzzy model, the tool is configured in MATLAB2018**a** [26]. MATLAB [1,27], is a multi–paradigm computing tool, that enables the modelling of real-time complex engineering solutions. Two secondary Interval Type-2 input parameters are used; i.e., Fire intensity due to temperature change $\widetilde{\mathbf{FI}}_{\mathrm{T}}$, and Fire intensity due to dissipated gases (CO_2, CO), $\widetilde{\mathbf{FI}}_{\mathbf{G}}$. The fire intensity interval output value $\widetilde{\mathbf{FI}}_{\mathbf{O}}$ of the IT2 TSK model is proposed to minimize the inherent errors of Type-1 (T1) fuzzy systems using a *type reduction* method, called the enhanced Karnik-Mendel (eKM) in range of [−1, 1]. Because eKM reduces the computational overload associated with fuzzy system design. The model was designed using the trim member function (trimf) using six sparse inference rules. NB: Flame presence = "True" for all fuzzy inference rules, else = "False". To determine the best-fit dataset of the IT2 TSK fuzzy model, a linear regression method is used to evaluate the datasets for improved accuracy. To compute the accuracy, error metric parameters, namely; the mean absolute error (**MAE**), mean square error (**MSE**), root mean square error (**RMSE**), and the coefficient of determination ($\mathbf{R^2}$), are used to determine the quality of the best choice of fit data to the model. For N = 17; N denotes the number of Interval Type-2 rule outcomes being sampled. The obtained dataset with the lowest RMSE value, is identified as the best fit dataset for the model in order to determine the operating efficiency and accuracy of the proposed Interval Type-2 fuzzy model.

3.1 Second Order Fuzzy Associative Matrix (2FAM)

The fuzzy associative matrix (FAM) is a content addressable memory for storing the fuzzy inference rules of a particular associated fuzzy model [28,29]. The study used the 2FAM method, with the Interval Type-2 fuzzy input sets as crisp input values for the proposed TSK model. With the second-order derivatives, the output fuzzy values of Type-1 (T1) fuzzy sets are converted into Type-2 (T2) input values. Note that, Type-2 fuzzy systems have gained popularity due to the fact that inherent errors created by Type-1 (T1) systems can be minimized by Type-2 fuzzy systems [27,30]. This improves the models' accuracy, by allowing them to create flawlessly functioning fuzzy systems in real time. Type-1 systems are denoted by **A**, and the Type-2 fuzzy associative members or elements are denoted by $\hat{A}$ [28,31] of comparable second order as per Dr. Loft Zadeh. For n = 1, 2, 3, …, N, then the associated order n can be explicitly defined. Thus, the Interval Type-2 TSK fuzzy control model's corresponding 2FAM sparse inference rules are then defined in Table 2. **NB:** The model utilizes six sparse rules to reduce the high computational overloads associated with Type-2 fuzzy system design.

Table 2: The proposed derived IT2 TSK sparse fuzzy inference rules (FIR) with output value ($\widetilde{\mathbf{FI_O}}$)

	Type-1 input variables		Interval Type-2 TSK output variables	
Rule No.	($\widetilde{\mathbf{FI_T}}$)	($\widetilde{\mathbf{FI_G}}$)	($\widetilde{\mathbf{FI_O}}$)	"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

Note: Proposed Optimized IT2 TSK Fire Intensity Output denoted by $\widetilde{\mathbf{FI_O}} = \{VL, L, M, H, VH\}$.

3.2 Proposed Interval Type-2 TSK Sparse Fuzzy Inference Rules (FIR) Design

Using the FAM method, as discussed in Section 3.1 above, we can further derive six (6) corresponding Interval Type-2 TSK sparse fuzzy inference rules for the proposed model.

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

The proposed IT2 TSK model utilizes two inputs $\widetilde{\mathbf{FI_T}}$, $\widetilde{\mathbf{FI_G}}$ and output $\widetilde{\mathbf{FI_O}}$ parameters to investigate the performance behaviour of the proposed Interval Type-2 TSK model. The universe of discourse for the various crisp interval inputs and output parameters is defined in Tables 3 and 4, respectively.

Table 3: Crisp interval input $\widetilde{\mathbf{FI_T}}$, $\widetilde{\mathbf{FI_G}}$ parameters considered for the proposed IT2 TSK fuzzy model

Crisp input values	Fuzzy input parameters	Fuzzy domain range (%)	Universe of discourse MF
Fire intensity due to temp. change ($\widetilde{\mathbf{FI_T}}$)	{Low, moderate, high}	[1–100] or [0–1]	{0–40, 40–80, 80–100} or {0–0.4, 0.4–0.8, 0.8–1}
Fire intensity due to gas dissipated ($\widetilde{\mathbf{FI_G}}$)	{Very low, low, moderate, 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: Crisp output ($\widetilde{\mathbf{FI_O}}$) parameter considered 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 ($\widetilde{\mathbf{FI_O}}$)	{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}

4 Algorithm Design Procedure

In Fig. 2, a schematic design of Mamdani's Type-1 fuzzy-based algorithms is defined by Lule et al. [1]. The fire intensity due to temperature change ($\mathbf{EFIP_1}$) and fire intensity due to the dissipated gases, i.e., (CO_2, CO), (**$EFIP_2$**), are Mamdani's Type-1 fuzzy outputs. For effective fire detection, the fire detection algorithms consider temperature, humidity, CO_2, CO, and flame parameters. Through the process of oxidation, oxygen reacts with carbon present in any burning material to give two dissipated gases, namely; CO_2 and CO. The fuzzy algorithms' schematics assume the threshold values ***Th*** and ***Thg*** to determine the minimal values of temperature rise and, gases dissipated, respectively, due to combustion. ***FI*** is the optimal fire intensity detection value of $\left(\widetilde{FI_O}\right)$ obtained by the proposed Interval Type-2 TSK algorithm.

Algorithm 1: The Estimated Fire Intensity Prediction (**$EFIP_1$**) Due to Temperature Change

```
Initialize: Crisp Input: ΔT, ΔH;
Define: Crisp Output: EFIP1;
Initialize: Set_Flame ←"True';
Define:  Th //As the Threshold Value for Temperature;
Apply the Type-1 Fuzzy Logic Construct:
while (ΔT > Th)
{//Apply Fuzzy Inference Rules
if (ΔT is Low AND ΔH is Dry)
then EFIP1 ← "LOW"
Else if (ΔT is Medium AND ΔH is Optimal)
then EFIP1 ← "MODERATE"
Else if (ΔT is Very Low AND ΔH is Optimal)
then EFIP1 ← "LOW"
Else if (ΔT is High AND ΔH is Dry)
then EFIP1 ← "HIGH"
Else if (ΔT is Medium AND ΔH is Dry)
then EFIP1 ← "MODERATE"
Else if (ΔT is Very High AND ΔH is Moist)
then EFIP1 ← "LOW"
Else if (ΔT is Very High AND ΔH is Optimal)
then EFIP1 ← "HIGH"
Else if (ΔT is Very High AND ΔH is Dry)
then EFIP1 ← "HIGH"

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

Algorithm 2: The Estimated Fire Intensity Prediction (**$EFIP_2$**) Due to Gas Dissipated.

```
Initialize: Crisp Input: ΔCO2, ΔCO, ΔO2;
Define: Crisp Output: EFIP2;
Initialize: Set_Flame ← "True';
Define: Thg; //As the Threshold Value for Gas Dissipated;
Apply Type-1 Fuzzy Logic Construct:
while (ΔCO2 > Thg)
{//Apply the Fuzzy Inference Rules
if (Δ CO2 is Low AND ΔCO is Low AND ΔO2 is Low)
then EFIP2 ← "L"
Else if (Δ CO2 is Low AND ΔCO is Medium AND ΔO2 is Medium)
then EFIP2 ←"M"
Else if (Δ CO2 is Medium AND ΔCO is Medium AND ΔO2 is Medium)
then EFIP2 ← "H"
Else if (Δ CO2 is High AND ΔCO is Dry AND ΔO2 is Low)
then EFIP2 ← "HIGH"
Else if (Δ CO2 is Low AND ΔCO is Dry AND ΔO2 is Low)
then EFIP2 ← "VH"
Else if (Δ CO2 is Low AND ΔCO is Dry AND ΔO2 is Low)
then EFIP2 ← "VH"
Else if (ΔCO2 is Very High AND ΔCO is Optimal AND ΔO2 is Low)
then EFIP2 ← "HIGH"
Else if (Δ CO2 is Very High AND ΔCO is Dry AND ΔO2 is Low)
then EFIP2 ← "HIGH"
              .... Rule n
End if
}
End while Loop
```

Figure 2: Mamdani's Type-1 fuzzy algorithms for fire intensity due temperature change (**$EFIP_1$**) and dissipated gas (**$EFIP_2$**), respectively [1]

4.1 Algorithm Assumptions Considered

Several assumptions are made by the proposed algorithm to ensure an optimal fire intensity detection value ($\widetilde{\mathrm{FI}_{\mathrm{O}}}$), realized:

i. Three key parameters for fire combustion are considered, namely; temperature (**ΔT**), and two by-products of dissipated gases; carbon dioxide (**ΔCO_2**), and carbon monoxide **(ΔCO)**.

ii. To reduce the computational overload associated with Type-2 fuzzy systems, six sparse inference fuzzy rules are used to optimize the performance of the overall fire intensity detection value of $\left(\widetilde{\mathrm{FI}_{\mathrm{O}}}\right)$.

iii. Note that humidity (**ΔH**) is not a key parameter for combustion due to its high dependency on temperature change and pressure within the surrounding environment. Note that for each inference rule, flame presence is a boolean probability equal to "True" or "False". Because of the high computational cost overheads associated with Type-2 fuzzy systems, output processing with centroid type reduction and defuzzification methods may cause unnecessary bottlenecks on Interval Type-2 fuzzy systems. Hence, alternative approaches, such as the Nie-Tan method [32,33], can be suggested.

4.2 Proposed Fire Intensity Detection Algorithm Procedure Based on IT2 TSK Fuzzy Approach

Algorithm 3: The Proposed Lightweight Fire Intensity Detection Algorithm Based on the IT2 TSK Fuzzy Model.

1. **Begin:**
2. **Initialize:** ΔT, ΔH, ΔCO_2, ΔCO;
3. Define: $\widetilde{\boldsymbol{FI}_O} = \mathbf{FI}$;
4. **Set Boolean**: setFlame0←0, setFlame1←1;
5. **if** fire is detected?
6. **True:** set **Flame1** ←**1**; **go to**: Step 11
7. else
8. **False: setFlame0** ← **0**; **go to**: Step 3
9. **do** {
10. **Define:** ΔT ← {L, M, H},
11. **Define:** ΔCO_2 ← {L, M, H};
12. { //Applying Fuzzy: For dissipated gases i.e., ΔCO_2 ΔCO
13. **if** (ΔT==" **L**" AND ΔCO_2=="**VL**" or CO=="**VL**")
14. **then** FI ← "**VL**"
15. **Else if** (ΔT==" **L**" AND ΔCO_2==" **L**" or CO==" **L**")
16. **then** FI ← " **L**" next
17. **Else if** (ΔT=="**M**" AND ΔCO_2=="**M**" or CO=="**M**")
18. **then** FI ← "**M**" next
19. **Else if** (ΔH=="**M**" AND ΔCO_2=="**H**" or CO=="**H**")
20. **then** FI ← "**H**"
21. **Else if** (ΔT=="**H**" AND ΔCO_2==" **VH**" or CO==" **VH**")
22. **then** FI ← "**VH**"
23. **End if**
24. }

(Continued)

Algorithm 3 (continued)	
25.	Output Value: **FI;**
26.	}
27.	**while** (ΔT < Th && (ΔCO_2 > Thg); **go to**: Step 3
End Loop:	

4.3 Fire Intensity Detection Model Using Interval Type 2 TSK Fuzzy Approach

In Fig. 3, the framework of the fire intensity detection model is made up of temperature, humidity, CO_2, and CO as data acquisition units, an optimized IT2 TSK model training unit, and a fire status decision-making unit. The obtained dataset is then trained using the IT2 TSK fuzzy model which is integrated with an intelligent fire intensity detection algorithm to determine an informed "fire status" decision due to the surrounding environment.

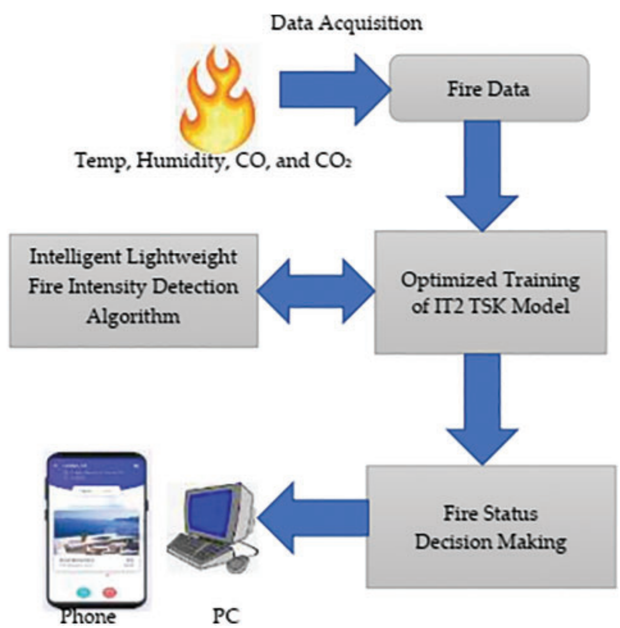


Figure 3: Proposed breakdown of the IT2 TSK fuzzy detection model with "fire status" decision making

5 Relational Mathematical Operations Theory and Notations in Type-2 Fuzzy Systems

A non-deterministic truth degree with imprecision and uncertainty for each set of elements is defined in Type-2 fuzzy set. Fuzzy inference systems utilize fuzzy reasoning and a set of principles to map fuzzy inputs to outputs. This method applies in a variety of application domains, like computer vision, pattern recognition, and intrusion detection. T1 systems represent the membership, as the membership of each element in a fuzzy set, whereas Interval Type-2 fuzzy sets represent the membership as crisp intervals bound by the range of $[-1, 1]$ [34–36]. Type-1 fuzzy systems have been used in a variety of fields, but they are most commonly associated with noisy data and extremely large uncertainty error limits as represented in their inference rule consequents [37,38]. Thus, from the principle of fuzzy set theory, the application of Interval Type-2 TSK fuzzy inference systems can be correlated using relational mathematical theoretical representations.

Let U, be the initial universe of objects, E_U, the set of parameters about the objects, P(U), the power set of U such that: $A \subseteq E$. Molodtsv [39] defined a set of the pair (F, A) called, the soft set over U, where F is a mapping given by: F: A → P(U). For $\varepsilon \in$ A, F(ε) is defined as a set of ε-approximate elements of the soft set (F, A). Type-2 fuzzy sets denoted by $\tilde{A}$, are also characterized by a general Type-2 membership function for which, $\mu\tilde{A}$ (x, U), such that: U defines a finite and non-empty set, which is referred to as a universe of discourse [40]. The membership function associates each element $x \in U$, with a value in the interval [0, 1].

$$\text{Hence; UxI} \rightarrow \text{I where; } x \in, I = [0, 1] \text{ and } \mu \in_x \subseteq I$$

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

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

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) [41].

5.1 Operations of General Type-2 Fuzzy Sets

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

$$\tilde{A} = \int_{x\in u}\frac{\mu\tilde{A}\,(x)}{x}\int_{x\in u}\frac{\left[\int_{x\in J_X^u} f_x\,(u)/u\right]}{x},\ J_x^u \subseteq I \qquad \widetilde{B} = \int_{x\in u}\frac{\mu\tilde{B}\,(x)}{x}\int_{x\in u}\frac{\left[\int_{\gamma\in J_X^\gamma} g_x\,(\gamma)/\gamma\right]}{x},\ J_x^\gamma \subseteq I \tag{2}$$

Hence, applying the general type-2 fuzzy operations to the aforementioned fuzzy sets, defined by Eq. (2), i.e., union, intersection, and complement, yields Eqs. (3)–(5), respectively, which can be explicitly reduced as follows:

$$\mu_{\tilde{A}\,u\,\tilde{B}}\,(x) = \int_{u\in j_X^u}\int_{\gamma\in j_X^\gamma}\frac{[f_x(u) \wedge g_x(u)]}{u \vee \gamma} = U_{\tilde{A}}\,(x) \sqcup U_{\tilde{B}}\,(x)\,,\ x\in U \tag{3}$$

$$\mu_{\tilde{A}\,n\,\tilde{B}}\,(x) = \int_{u\in j_X^u}\int_{\gamma\in j_X^\gamma}\frac{[f_x(u) \wedge g_x(u)]}{u \wedge x} = U_{\tilde{A}}\,(x)\,U_{\tilde{B}}\,(x)\,,\ x\in U \tag{4}$$

$$\mu_{\sim\tilde{A}}\,(x) = \mu_{\tilde{A}}\,(x) = \int_{u\in j_X^u}\frac{f_{x\,(u)}}{1-\mu} \tag{5}$$

where $\wedge$ is the t-norm minimum operator, $\vee$ is the maximum operator, and $\sqcup$ the joint operation, $\mu_{\tilde{A}\,u\,\tilde{B}}(x)$, $\mu_{\tilde{A}}(x)$, $\mu_{\tilde{B}}(x)$ are the secondary membership functions, and for all belonging to Mamdani's Type-1 fuzzy sets [39,41].

5.2 IT2 TSK Fuzzy Inference Systems vis-à-vis Decision Making

An Interval Type-2 fuzzy set (FS) can be characterized by the Eq. (6) below:

$$\widetilde{A} = \int_{x\in X}\left\{\int_{\mu\in J_x} 1/\mu\right\}/x,\ J_x \subseteq\ [0\ 1] \tag{6}$$

The secondary grades of $\widetilde{A}$ is equal to 1: 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 Interval Type-2 fuzzy set can therefore be best described by having the lower (LMF) or $\underline{u}_{\tilde{A}}$ (x) and the upper membership functions (UMF) or $\overline{u}_{\tilde{A}}$ (x). Therefore, the given shaded region (ref. Fig. 4), between the LMF and

UMF is called the "*Footprint of Uncertainty (FOU)*". Thus, FOU represents a third-dimensional value of the membership function (MF) at each point on its two-dimensional domain such that [42]:

$$\mathrm{FOU}\left(\widetilde{A}\right) = U_{x \in X}\left[\underline{u}_{\widetilde{A}}(x), \overline{u}_{\widetilde{A}}(x)\right] \tag{7}$$

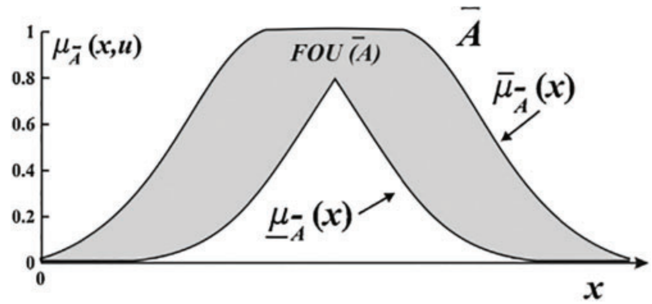


Figure 4: Shows the interval Type-2 fuzzy set with a shaded region known as the FOU [42]

From Eq. (6), using the Interval Type-2 TSK fuzzy systems rules approach, the firing strength, determines the minimal probability for a given fire status. Thus, the fire status can be determined using the **IF** … **THEN** structure for the fuzzy inference consequent decision evaluation. Upon this background, consider a typical Type-1 TSK sparse rules-based approach comprised of n fuzzy inference rules [43]:

R_1: **IF** x_1 *is* A_1^1 and … x_k *is* A_k^1 and … x_q *is* A_q^1 **THEN** $y = \boldsymbol{f}_1\boldsymbol{x}_1^1(\ldots x_q^1,)$,

…

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

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

Alternatively, assuming the IT2 TSK sparse rules are comprised of n rules, then a zero or first-order polynomial function can be derived such that:

R_1: **IF** x_1 *is* $\widetilde{A}_1^1$ and … x_k *is* $\widetilde{A}_k^1$ and … **THEN** $y = \widetilde{p}_0^1 + \widetilde{p}_1^1 x_1^1 + \ldots \widetilde{p}_k^1 x_k^1$

R_i: **IF** $\boldsymbol{x}_1$ *is* $\widetilde{A}_1^i$ and … x_k *is* $\widetilde{A}_k^i$ and … **THEN** $y = \widetilde{p}_0^i \widetilde{p}_1^i x_1^i + \ldots \widetilde{p}_k^i x_k^i$

…

R_n: **IF** x_1 *is* $\widetilde{A}_1^n$ and … x_k *is* $\widetilde{A}_k^n$ and … **THEN** $y = \widetilde{p}_0^n + \widetilde{p}_1^i x_1^n + \ldots \widetilde{p}_k^n x_k^n$

where $\widetilde{A}_j^i$ $(j \in \{1, \ldots, k\}$ and $i \in \{1, \ldots, n\})$ is defined as an Interval Type-2 fuzzy set having an input variable $\boldsymbol{x}_j$ in the $\boldsymbol{i}^{th}$ rule, giving a consequent in the crisp polynomial function as:

$y = f_i\left(x_j, \ldots, x_k\right) = \widetilde{p}_0^n + \widetilde{p}_i^i x_1^n \ldots \widetilde{p}_k^n x_k^n$ where $\widetilde{p}_j^i$ are crisp intervals or consequent parameters for a given universe of discourse such that; $O\left(\widetilde{A}_1^* \ldots \widetilde{A}_k^*\right)$, $\widetilde{A}_j^i$, the antecedent value of the rule R_i. Using the related IT2 TSK fuzzy model approach of Jie Li et al. [44] the approximate firing strength ($\overline{\boldsymbol{\alpha}}_i$), of matching degree s and antecedent variable x_j, using a t-norm operator $*$ can be deduced to the Eq. (8):

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

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

$$(\bar{\alpha}_i) = s\left(\overline{\tilde{A}}_1^i, \overline{\tilde{A}}_1\right) \wedge \ldots \wedge s\left(\overline{\tilde{A}}_k^i, \overline{\tilde{A}}_k\right) \tag{8}$$

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

$$Y = [y_l, y_r] \int_{y^1} \cdots \int_{y^m} \cdot \int_{f^1} \cdots \int_{f^m} \frac{1}{\frac{\sum_{i=1}^{m} f^i y^i}{\sum_{i=1}^{m} f^i}} \tag{9}$$

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

$\boldsymbol{y}^i = \left[\boldsymbol{y}_i^i, \boldsymbol{y}_r^i\right]$ is the centroid of the Type-2 interval fuzzy set in the consequent part. Karnik et al. [45] showed that two endpoints are dependent on the mixture of f^i and $\bar{f}^i$ values can be determined as:

$$\begin{aligned} \boldsymbol{y}_r &= y_r\left(\underline{f}^1, \ldots, \underline{f}^R, \bar{f}^{R+1} \ldots \bar{f}^m, y_r^1, y_r^m\right) \\ y_i &= y_i\left(\bar{f}^1, \ldots, \bar{f}^m, \underline{f}^{l+1} \ldots \underline{f}^m, y_i^1, y_i^m\right) \end{aligned} \tag{10}$$

NB: (y_r, y_i) are determined by using Eq. (10). A special iterative formula was then developed by Mendel et al. [46] to produce the computational values of y_r(max) and $y_{i(min)}$ as:

$$\begin{aligned} y_r &= \frac{\sum_{i=1}^{R} \underline{f}_i y_i^r + \sum_{i=R+1}^{m} \bar{f}_i y_i^r}{\sum_{i=1}^{R} f_{-i} + \sum_{i=R+1}^{m} \bar{f}_i} \\ y_i &= \frac{\sum_{i=1}^{L} \bar{f}_i y_i^l + \sum_{i=L+1}^{m} \underline{f}_i y_i^l}{\sum_{i=1}^{L} \bar{f}_i + \sum_{i=L+1}^{m} \underline{f}_i} \end{aligned} \tag{11}$$

Thus, the switch points can be determined by using Karnik-Mendel's (KM) algorithm [45,46]. Therefore, the crisp outputs in the defuzzification layer can then be computed as follows:

$$y = \frac{y_r + y_i}{2} \tag{12}$$

5.3 Type Reduction

Type Reduction (TR) is a phase used to defuzzify the Type-2 fuzzy sets that transform Type-2 into Type-1 fuzzy systems. T1 and IT2 fuzzy systems differ in that IT2 fuzzy systems employ an extra TR procedure to process Interval Type-2 systems. The KM TR method is widely used to calculate the type-reduced sets iteratively [47]. 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) [26]. The enhanced KM algorithm is used in the study to reduce computational overload and significantly captures most features of the IT2 fuzzy model, such as adaptability and stability. The major bottleneck of Type-2 fuzzy systems is output processing using the centroid TR and defuzzification method. Since KM algorithms are associated with high computational costs, this may hinder their real-time application [48]. Thus, to compromise between the speed, computational overload, and complexity, other methods were proposed, i.e., the Nie-Tan method, to compute the output of the IT2 TSK fuzzy system [33,49]. 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	Compute y_r
1. **Initialize**	1. **Initialize**
$a = \sum_{n=1}^{N} \underline{y}^n \underline{f}^n$	$a = \sum_{n=1}^{N} \overline{y}^n \underline{f}^n$
$b = \sum_{n=1}^{N} \underline{f}^n$	$b = \sum_{n=1}^{N} \underline{f}^n$
$L = 0$	$R = N$
2. **Compute** y_l	2. **Compute** y_r
$L = L + 1$	$a = a + \overline{y}^R \left(\overline{f}^R - \underline{f}^R\right)$
$a = a + \underline{y}^L (\overline{f}^L - \underline{f}^L)$	$b = b + \overline{f}^R - \underline{f}^R$
$b = b + \overline{f}^L - \underline{f}^L$	$y_r = a/b$
$y_l = a/b$	$R = R - 1$
3. **if** ($y_l \leq y^{L+1}$), stop	3. **if** $y_r \geq y^R$, stop;
otherwise, go to: Step 2	**otherwise, go to**: Step 2

Then, the Nie-Tan method can therefore be mathematically defined using the Eq. (13) below:

$$y = \frac{\sum_{n=1}^{N} y^n \left(\underline{f}^n + \overline{f}^n\right)}{\sum_{n}^{N} \left(\underline{f}^n + \overline{f}^n\right)} \tag{13}$$

6 Simulation Experiment Setup

Fig. 5 shows an Interval Type-2 Takagi Sugeno Kang (TSK) fuzzy design view of the model editor using MATLAB. A free open–source MATLAB fuzzy logic toolbox is carefully configured with varying parameter settings as defined in Table 5 and successfully integrated into the MATLAB2018a environment for proper functioning. The tool is widely used in the modeling and simulation of Type-2 fuzzy systems [47]. The model uses a TSK inference system to ensure higher performance is realized for the proposed fire detection algorithm [50]. Through "*fuzzification*", crisp inputs are defined in Table 3. The Enhanced Karnik–Mendel algorithm is used to minimize the computational overload in Type-2 systems [45]. Through the "*defuzzification*" process, the performance outcome of the proposed IT2 fuzzy model can be obtained.

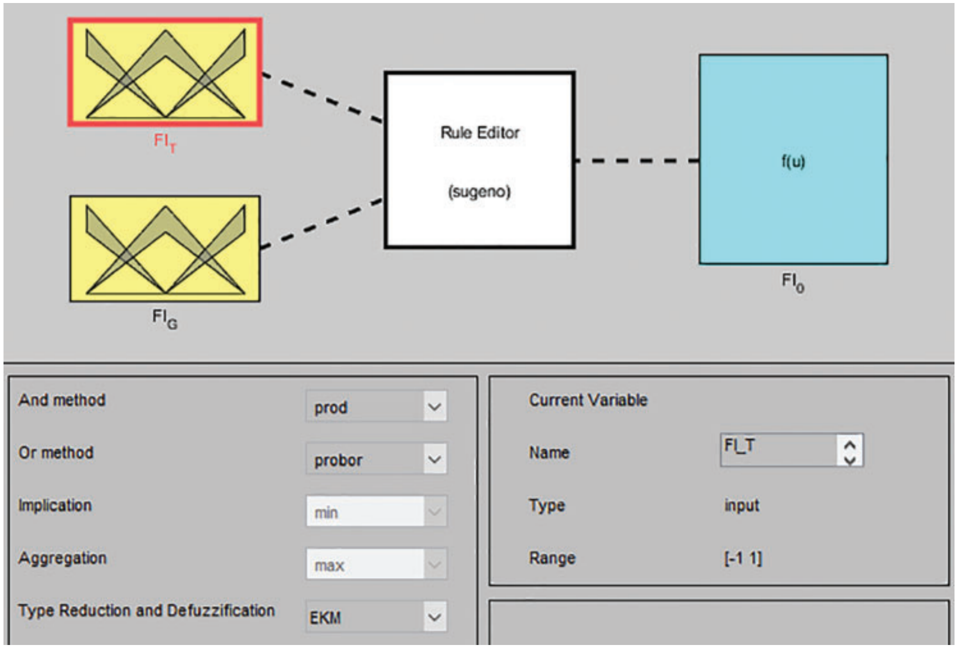


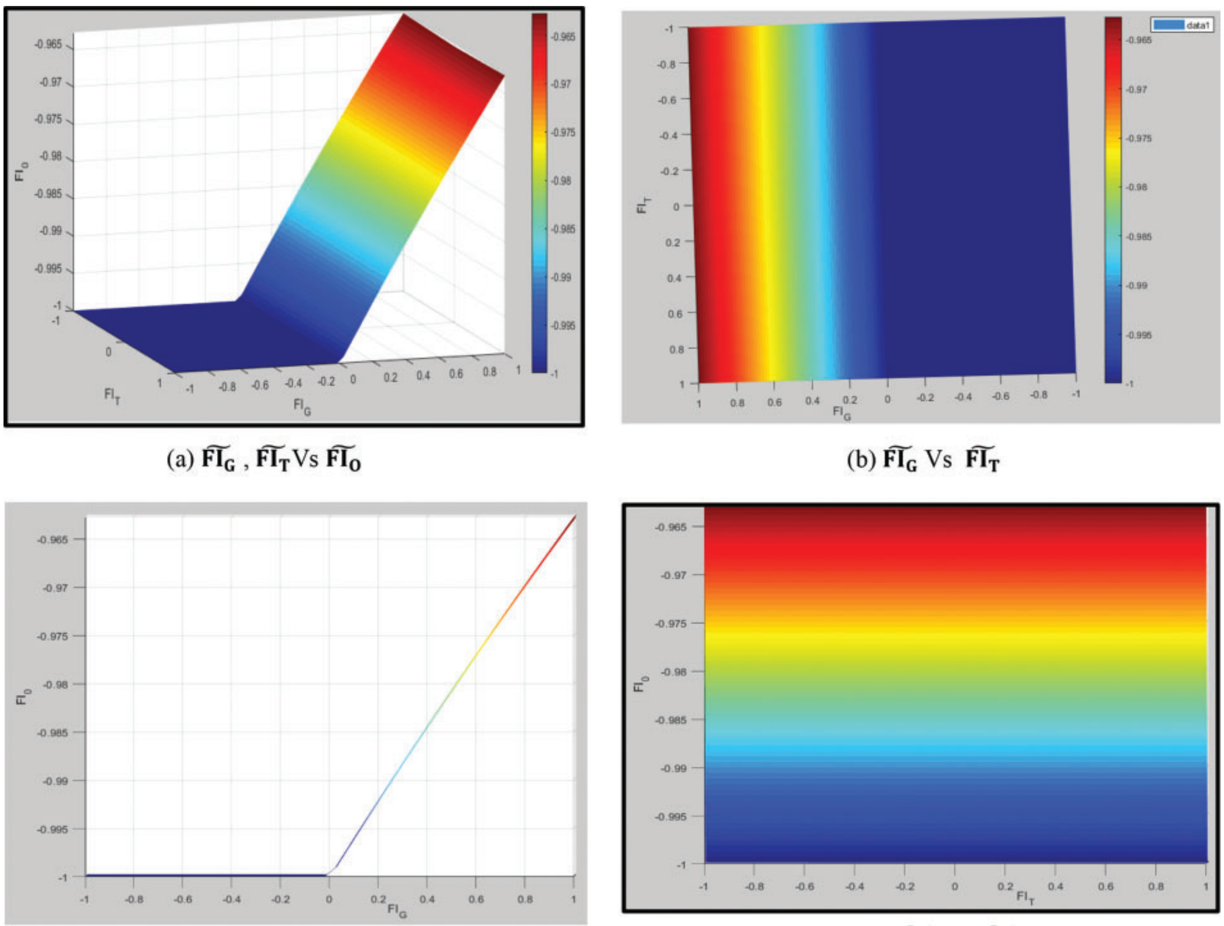
Figure 5: Main model editor of IT2 TSK with crisp interval inputs: $(\widetilde{\mathbf{FI}}_{\mathbf{T}})$, $(\widetilde{\mathbf{FI}}_{\mathbf{G}})$ and crisp output parameter: $(\widetilde{\mathbf{FI}}_{\mathbf{O}})$, the optimized fire intensity value

Table 5: Experimental setup configuration settings

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 interval 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 $\widetilde{\mathbf{FI}}_{\mathbf{O}}$ = {Very low, low, moderate, high, very high}, 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: 802.11 g/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)	

7 Results and Discussion

In Figs. 6a–6d, results were obtained by integrating a free open-source fuzzy toolbox of Interval Type-2 within the MATLAB 2018a environment [27]. The tool was used to investigate the IT2 TSK model's performance behaviour. Two input parameters are used; fire intensity due to gases dissipated $\widetilde{FI}_G$ and fire intensity due to temperature change $\widetilde{FI}_T$. The optimized fire intensity output $\widetilde{FI}_O$ is determined by the correlation between $\widetilde{FI}_G$ vis a vis $\widetilde{FI}_T$. Based on six significant IT2 TSK sparse rules defined in Table 1, the eKM type reduction algorithm was used to reduce the computational complexity associated with Type-2 fuzzy systems.



(a) $\widetilde{FI}_G$, $\widetilde{FI}_T$ Vs $\widetilde{FI}_O$

(b) $\widetilde{FI}_G$ Vs $\widetilde{FI}_T$

(c) $\widetilde{FI}_G$ Vs $\widetilde{FI}_O$

(d) $\widetilde{FI}_T$ Vs $\widetilde{FI}_O$

Figure 6: (a–d) show a 2D, 3D surfaces control view outputs for the IT2 TSK fuzzy model with continuous discrete color pattern separations using MATLAB 2018a

Several insights can be drawn:

i. The fire intensity surface control results of the Interval Type-2 TSK fuzzy model range from [−1, 1]. The obtained linear discrete model pattern (ref. Fig. 6a) shows changes in $\widetilde{FI}_G$ or $\widetilde{FI}_T$ gradually influence the output value of $\widetilde{FI}_O$. E.g., an increase in both $\widetilde{FI}_G$ and $\widetilde{FI}_T$ significantly increases $\widetilde{FI}_O$. Thus, higher changes in $\widetilde{FI}_G$ or $\widetilde{FI}_T$ increase the risk of fire intensity due to combustion. Also, Figs. 6b–6d show a higher $\widetilde{FI}_T$ with increasing temperature change, results in a higher risk of dissipated gases of $\widetilde{FI_G}$. Hence, the increased output performance of $\widetilde{FI_O}$ vis-à-vis increased $\widetilde{FI_T}$ and $\widetilde{FI_G}$.

ii. In Fig. 6c, an increase in fire intensity due to dissipated gasses $\widetilde{FI_G}$, raises the output value of $\widetilde{FI_O}$ due to increased gas combustion. Similarly, in Fig. 6d, an increase in temperature change $\widetilde{FI_T}$ increases the value of $\widetilde{FI_O}$. Hence, general Type-2 fuzzy systems significantly improve the output design of the Interval Type-2 TSK model. In Figs. 6b–6d, increased temperature yields higher $\widetilde{FI_O}$ due to an increased fire intensity risk associated with temperature change. Likewise, Fig. 6c shows increased gases dissipated, yields higher $\widetilde{FI_O}$ (Greater fire intensity from blue to dark red region).

Table 6 and Fig. 7 depict a graphical representation of a set of absolute values taken to study the correlation between $\widetilde{FI_T}$, $\widetilde{FI_G}$ against values of $\left(\widetilde{FI_O}\right)$, for the Interval Type-2 TSK fuzzy model. The firing strength is computed using the sparse inference rules approach. The Enhanced Karnik-Mendel (eKM) algorithm gives a smooth, stable curve (dashed line) of the output fire intensity $\widetilde{FI_O}$, with an accuracy rate of 98.2%. Thus, the heat transferred during combustion increases $\left(\widetilde{FI_O}\right)$ with the proposed IT2 TSK model. With regression analysis, an accuracy rate of **98.2%** is determined as the best-fit data for the model. Hence, a significant improvement of $\left(\widetilde{FI_O}\right)$ is realized using the IT2 TSK inference system compared to Mamdani's Type-1 fuzzy model in Lule et al. [1]. Also, a sudden drop or (unstable state) in temperature change is observed through $\widetilde{FI_T} = 0.7959$ to 0.02041, $\widetilde{FI_G} =$ 1 to 0.1429. Because of the inherent error uncertainties associated with the rule-based consequents in the fuzzy model. Secondly, the reduced levels of oxygen depleted due to combustion, reflect a decrease in the overall output performance of the fuzzy model. Thus, results show a subsequent drop in both temperatures and CO_2 concentration levels in the surrounding environment.

Table 6: Relationship between ($\widetilde{FI_T}$, $\widetilde{FI_G}$) and the optimized fire intensity output ($\widetilde{FI_O}$) using the absolute values in the normalized range [0–1]

Fire intensity due to temperature ($\widetilde{FI_T}$)	Fire intensity due to gas dissipated ($\widetilde{FI_G}$)	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

(Continued)

Table 6 (continued)

Fire intensity due to temperature ($\widetilde{FI_T}$)	Fire intensity due to gas dissipated ($\widetilde{FI_G}$)	Fire intensity output ($\widetilde{FI_O}$)
0.8776	0.7551	0.9713
0.6327	0.5102	0.9803

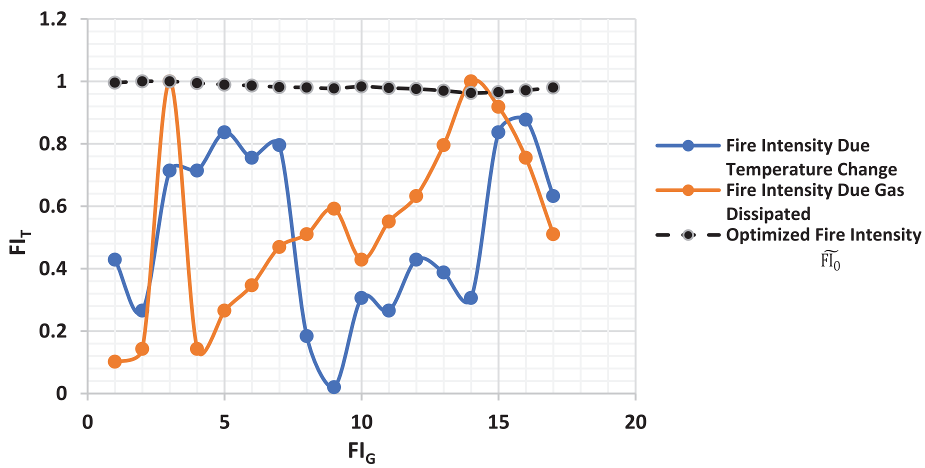


Figure 7: Evaluation of IT2 TSK fuzzy model with absolute values of $\widetilde{FI_T}$, $\widetilde{FI_G}$ *vs.* $\widetilde{FI_O}$ in the normalized range of [0–1]

In Table 7 and Fig. 8, useful insights are derived by plotting $EFIP_1$, $EFIP_2$ against values of $\widetilde{\mathbf{FI_O}}$;

Compared to the Interval Type-2 TSK output $\widetilde{FI_O}$, the $EFIP_1$ and $EFIP_2$ in Mamdani's Type-1 fuzzy systems yielded a lower (unstable) performance outcome. Mamdani's TI fuzzy systems have high uncertainty error bounds despite using a dense network of fuzzy inference rules. Therefore, the Interval Type-2 fuzzy model reduced the error bounds caused by the Type-1 fuzzy systems. Thus, the performance outcome of the model was significantly improved.

Therefore, the IT2 TSK fuzzy model value of $\widetilde{FI_O}$, greatly outperformed Mamdani's Type-1 inference models of ($EFIP_1$) and ($EFIP_2$) [1]. Mandani's Type-1 systems contain associated error uncertainties leading to low operating outcomes. The datasets presented in Expt. X–Z, generally show an improved accuracy output value of the IT2 TSK model equivalent to 98.2% for $N = 17$ sampled fuzzy rule outcomes.

Table 7: Extracted dataset results for Mamdani's Type-1 fuzzy outputs (**$EFIP_1$, $EFIP_2$**) *vs.* interval Type-2 TSK output value $\left(\widetilde{\boldsymbol{FI_o}}\right)$

S. No.	$EFIP_1$(%)	$EFIP_2$(%)	$\left(\widetilde{\boldsymbol{FI_o}}\right)$ (%)
1	17.6	47.8	99.5
2	18.3	63.2	100

(Continued)

Table 7 (continued)

S. No.	$EFIP_1$(%)	$EFIP_2$(%)	$(\widetilde{FI_O})$ (%)
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

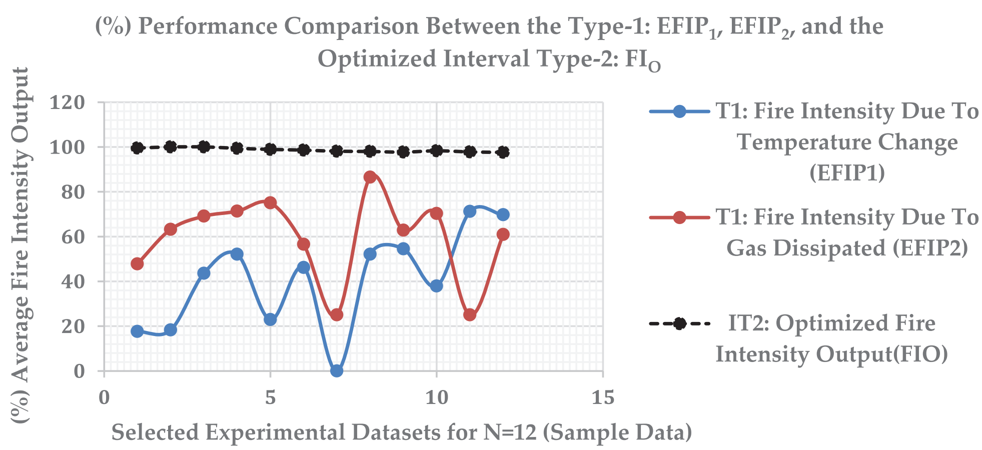


Figure 8: Mamdani's Type-1 fuzzy models (**$EFIP_1$**, **$EFIP_2$**) *vs.* the proposed interval Type-2 TSK Output $(\widetilde{FI_O})$

7.1 Performance Evaluation of the Proposed IT2 TSK Fuzzy Model Using Regression Analysis

Table 8 provides a detailed summary of the statistical metric parameters, i.e., MAE, MSE, RMSE, and R^2, used in the study to compare the performance outcome of each dataset for the model. Three experimental (Expt.) datasets, X, Y, and Z, are extracted from the IT2 TSK fuzzy model bound in the range of [1, −1]. With regression analysis, the best-fit dataset of the model is determined. Regression analysis is used in identifying the data with the greatest influence. A correlation is established between independent input variables of $\widetilde{FI_T}$ and, $\widetilde{FI_G}$, the dependent output $(\widetilde{FI_O})$, the expected outcome (E). The linear regression equations are then determined for various Expt. datasets (X, Y, and Z), as; $y = -0.2281x + 0.5215$; $y = 0.0802x + 0.3763$; and $y = -0.3025 + 0.8382$, respectively. Error metric parameters are used to compute the error deviations of the datasets to assess the accuracy of the predictions, defined; i.e., Mean Absolute Error $(MAE) = \sum \frac{|FI_0 - E|}{N}$; Mean Square

Error (MSE) $= \sum \frac{|FI_0 - E|^2}{N}$; and Root Mean Square Error (RMSE) $= \sqrt{\sum \frac{|FI_0 - E|^2}{N}}$ or $\sqrt{MSE}$, For $N = 17$, sampled fuzzy-based inference rule outcomes for the proposed Interval Type-2 TSK fuzzy model.

Table 8: Summary of the statistical measured parameters of MAE, MSE, R^2, and RMSE of the model

Expt. Datasets (X, Y, Z)	MAE	MSE	RMSE	R^2	Average accuracy outcome	For N = 17 interference 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**

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	0.4286	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. 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	−0.7143	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

(Continued)

Expt. Y (continued)

Expt. No.	FI_T	FI_G	FI_O	Expected, E	FI_O-E	$\|FI_O-E\|$	$\|FI_O-E\|^2$
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. Z: Experimental Dataset Z

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

7.2 Comparison between the Previous Works Done and the Proposed Solution

Table 9 provides a detailed comparison between the related works and the proposed IT2 TSK fuzzy model.

Table 9: Performance comparison between the proposed IT2 TSK fuzzy model and related works

	Zulkamain et al. [51]	Lule et al. [1]	Renzo et al. [52]	Li et al. [53]	Proposed IT2 TSK fuzzy model
Accuracy	90%	95.8%	91%	83%	**98.2%**
Method or techniques used	Uses fuzzy application methods	T1 Mamdani's fuzzy control systems	TI fuzzy control systems	Convolution neural network (CNN) models	Interval Type-2 (IT2) 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 algorithms based on CNN models.	Intelligent lightweight fire intensity detection algorithm for low-cost devices.

8 Limitations

Because of the inherent uncertainty errors present in fuzzy-based systems, Interval Type-2 fuzzy systems reduce the degree of membership and change the meaning of fuzzy words, which may have a significant impact on the model's overall decision-making and performance efficiency of the output value.

9 Conclusion and Future Works

In this paper, an Interval Type-2 TSK fuzzy model for an intelligent lightweight fire intensity detection algorithm with decision-making in low-power fire detection devices is presented. Using a multisensory design approach, the proposed method increased the model's accuracy rate to 98.2% while minimizing false alarms in fire detection systems or devices. Besides, Interval Type-2 fuzzy systems have a *footprint of uncertainty* (FOU) in their fuzzy sets, allowing them to further minimize the inherent errors associated with fuzzy system designs [27]. Hence, this solution can also be implemented in low-cost, low-power fire detection systems to notify the state or level of fire danger. Thus, the study shall assist the firefighting personnel in fully monitoring, comprehending, and mitigating any level of fire danger, allowing them to make informed and appropriate decisions about the fire suppression mechanisms to be used. Future work plans to implement a hardware-based solution for a low-cost fire detection system using an Adaptive Neural Fuzzy Inference System (ANFIS), which develops more accurate models combined with computational intelligence and fuzzy logic to provide more precise learning capabilities for effective fire detection, improving fire safety monitoring and protection of the market community by leveraging early warning alerts for safe evacuations. Thus, a foundation has been laid for the development of inbuilt low-power fire detection systems that are cost-effective and easily deployable by firefighters in developing countries to protect against fire accidents in marketplaces or public gathering areas.

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Availability of Data and Materials: All the data concerning fire outbreaks in Uganda can be obtained in published reports of the Uganda Police Force (UPF): https://www.upf.go.ug/publications/. All simulated datasets used have been extracted from the MATLAB 2018a modeling and simulation Experiments, all included in the manuscript.

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